Automated identification of slums in Hyderabad using high resolution satellite imagery

D i s s e r t a t i o n

zur Erlangung des akademischen Grades

Doctor rerum naturalium im Fach Geographie

eingereicht an der

Mathematisch-Naturwissenschaftlichen Fakultät II

der Humboldt-Universität zu Berlin

von

M.Sc. Oleksandr Kit

Präsident der Humboldt-Universität zu Berlin

Prof. Dr. Jan-Hendrik Olbertz

Dekan der Mathematisch-Naturwissenschaftlichen Fakultät II

Prof. Dr. Elmar Kulke

Gutachter:

Prof. Dr. Wolfgang Lucht
Prof. Dr. Antje Bruns
Dr. Andrew Tatem

Tag der Verteidigung: 13. Februar 2014

Acknowledgements

I was very delighted to meet and to work together with many extraordinary people during my years in Germany that led to this dissertation and express my sincere thanks and gratitude for their continuous support and encouragement.

I express my sincere thanks to Prof. Dr. Wolfgang Lucht for his consent to supervise this dissertation and seeing a potential in my research. My special thanks go to my academic supervisor Dr. Matthias Lüdeke, who invested great amounts of time and effort into supporting and supervising every step of my PhD project. I extremely appreciate his thoroughness and the very open and productive scientific debate culture he created in our group. I am very much indebted to Dr. Diana Reckien for fruitful discussions, inspiration and support in designing this research, quest for solutions and assessing the results. I esteem her professional vision that greatly shaped the course of my research.

I am grateful to many other members of my scientific family at Potsdam Institute for Climate Impact Research for productive discussions and fresh views into the problems and perspectives of this study, particularly to Prof. Dr. Jürgen Kropp, Lutz Meyer-Ohlendorf and Martin Budde. I also thank my colleagues at the GeoData Institute, University of Southampton, for their invaluable support and understanding. Thank you, Jason Sadler, Dr. Chris Hill and Dr. Craig Hutton.

This work would not be possible without the financial support from the Federal Ministry of Education and Research of Germany (BMBF) under the project “Future Megacities”.

I acknowledge the enormous role of my family back in Ukraine who gave me the opportunity to study. I am extremely grateful to my beloved wife Mira for her enormous support and patience both before and during this PhD project.

I devote this dissertation to my late grandmother Nadia Serediak, who shaped my path into science from very early years on.

Abstract

Slums are a pervasive feature of many urban regions in the global South, with India hosting the largest number of the global slum dwellers. Differences in slum definitions across countries and deficiencies of data collection are the cause of a large error margin in establishing slum population numbers and slum locations at a global, national and city scale. Very high resolution satellite imagery combined with advanced image processing methods constitute a powerful tool to address the paucity of this data, enabling delineation of formal and informal neighbourhoods on the basis of their distinct morphological features.

The main goal of this thesis is to develop an approach to automated identification of slums using sub-metre resolution satellite imagery, and to apply the new method to the slum-plagued South Indian megacity of Hyderabad. This dissertation establishes a multi-step satellite imagery analysis framework, which is capable of performing rapid identification of slums in Hyderabad without extensive ground surveys or manual image analysis. It is based on the relation of a specific range of spatial heterogeneity expressed through lacunarity to the probability of an area to be morphologically similar to the surface texture of a slum. The application of the proposed method has for the first time produced plausible, spatially coherent and politically unbiased slum coverage and slum population datasets for the whole of Hyderabad. The results expose inconsistencies in slum population data reporting and the slum recognition process currently in place in the city. The analysis of multitemporal remote sensing data indicates a considerable slum population increase in the metropolitan area of Hyderabad and provides an insight into spatiotemporal slum development patterns between the years 2003 and 2010.

This dissertation contributes to the body of knowledge on remote sensing of human settlements and advanced image processing techniques and presents an essential instrument to be used by a the United Nations bodies, national and city governments as well as non-governmental organisations engaged in slum-related work.

Zusammenfassung

Slums bilden einen wesentlichen Bestandteil vieler Stadtregionen des globalen Südens, wobei Indien die höchste Zahl an Slumbewohnern beherbergt. Die internationalen Unterschiede in der Definition des Begriffs "Slum" sowie Mängel bei der Datenerfassung haben eine hohe Fehlerwahrscheinlichkeit bei der Aufnahme von Slumbevölkerungszahlen und -standorten in globalem, nationalem und städtischem Maßstab zur Folge. Eine Kombination aus hochauflösenden Satellitenbildern und fortgeschrittenen Bildverarbeitungsmethoden stellt ein äußerst leistungsfähiges Instrument zur Behebung des bestehenden Datenmangels dar und ermöglicht die Erkennung formeller und informeller Siedlungen aufgrund ihrer morphologischen Merkmale.

Das Hauptziel dieser Dissertation besteht darin, eine Vorgehensweise zur automatischen Erkennung von Slums mit Hilfe von hochauflösenden Satellitenbildern zu entwickeln, und diese Methode in der indischen Metropole Hyderabad anzuwenden. Diese Arbeit entwickelt ein mehrstufiges Satellitenbildbearbeitungsverfahren, welches in der Lage ist, eine schnelle Slumerkennung in Hyderabad durchzuführen. Das Verfahren beruht auf dem Verhältnis zwischen einem bestimmten Bereich räumlicher Heterogenität, ausgedrückt durch Lakunarität, und der Wahrscheinlichkeit, dass die Struktur eines Gebietes der Oberflächenstruktur eines Slums entspricht. Die Anwendung der hier vorgeschlagenen Methode produzierte zum ersten Mal einen plausiblen, räumlich kohärenten und politisch unverzerrten Datensatz über Slumstandorte und Slumbevölkerung für das gesamte Stadtgebiet von Hyderabad. Die Ergebnisse verdeutlichen die Unstimmigkeiten bei der bisherigen Erfassung der Slumbevölkerungszahlen sowie bei der offiziellen Anerkennung von Slums. Die multitemporale Satellitenbildauswertung zeigt ein Wachstum der Slumbevölkerungszahlen im Großraum Hyderabad an und bietet Einblick in den zeitlich-räumlichen Slumwachstumprozess zwischen den Jahren 2003 und 2010.

Diese Dissertation stellt einen wissenschaftlichen Beitrag zu den Themen Fernerkundung der Siedlungen und fortgeschrittene Bildbearbeitungsmethoden dar und bietet den unterschiedlichsten Parteien, für welche Slumdaten von Bedeutung sind, ein wichtiges Instrument.

Contents

Acknowledgements 2

Abstract 3

Zusammenfassung 4

Contents 5

List of figures 7

List of tables 8

Abbreviations 9

Chapter I: Introduction 10

1. Urban world 10
2. Urban slums 11
3. Remote sensing of cities and slums 12
4. Hyderabad 15
5. Rationale and research questions 17

Chapter II: Texture-based identification of urban slums in Hyderabad, India using remote sensing data 20

Abstract 21

1. Introduction 21
2. Study area 27
3. Methodology 29
   3.1. Data source 29
   3.2. Data preparation 29
      3.2.1 Method 1 (PCA-based) 30
      3.2.2 Method 2 (Line detection-based) 31
   3.3. Lacunarity calculation 32
4. Results 33
5. Discussion 35
6. Summary and conclusions 37
7. Acknowledgements 38

Chapter III: Defining the bull's eye: satellite imagery-assisted slum population assessment in Hyderabad/India 39

Abstract 40

1. Introduction 40
2. Study area 43
3. Methodology 43
4. Results 48
5. Discussion 50
6. Summary and conclusions 52
7. Acknowledgements 53

Chapter IV: Automated detection of slum area change in Hyderabad, India using multitemporal satellite imagery 54

Abstract 55
1. Introduction 55
2. Study area 57
3. Methodology 59
4. Results 64
5. Discussion 68
6. Summary and conclusions 70
7. Acknowledgements 72

Chapter V: Assessment of climate change-induced vulnerability to floods in Hyderabad/India using remote sensing data 73

Abstract 74
Introduction 74
1. Flood risk assessment for Hyderabad 75
2. Identification of flood prone areas 76
3. Identification of location of informal settlements 77
4. Conclusions 82

Chapter VI: Conclusions 84

1. Research questions answered 84
2. Application of results 88
3. Future perspectives 91

Bibliography 92

List of figures

Figure 1. Location of Hyderabad in India. 15
Figure 2. Sample natural colour image and binary matrix pca_127 (both covering Punjagutta area of Hyderabad) 31
Figure 3. Sample natural colour image and binary matrix line_70 (both covering Punjagutta area of Hyderabad) 31
Figure 4. Slum detection flowchart. 34
Figure 5. Slum Locations in Hyderabad (red areas) and georeferenced field photographs of Rasolpoora slum in the northern and Nagamiah Kunta slum in the eastern part of the city (photo credit: Martin Budde/PIK) 35
Figure 6. Location of Hyderabad in India 43
Figure 7. Algorithm validation. X-axis: lacunarity value of a 60 m × 60 m urban subarea of Hyderabad. Y-axis: probability that a subarea with a lacunarity value within the respective 0.05 interval represents slum morphology (after Kit et al. 2012). 45
Figure 8. Algorithm verification. Image A: Estimated percentage of slum population relative to total ward population. Image B: Percentage of slum population relative to total administrative circle population. 48
Figure 9. Circle-wise comparison of multiple-source slum population figures. 49
Figure 10. Official slum maps of Hyderabad according to HUDA, 2003 (left) and GHMC, 2005 (right). 58
Figure 11. Comparison of original satellite imagery (a), Laplacian of Gaussian (b), Canny (c) and LSD (d) binarisation algorithms for 2003 and 2010 scenes. 62
Figure 12. Slum identification algorithm flowchart. 63
Figure 13. Automatically identified slums of Hyderabad in 2003 and 2010. 64
Figure 14. Example of combination of Canny and LSD algorithms for slum identification. 65
Figure 15. Establishment of a slum at I.S.Sadan area. 66
Figure 16. Ground truthing sites (green – positively identified slums, red – false identification; 1-10: sites by Bostel 2012, A-C: sites by Kit et al. 2012). 67
Figure 17. Current distribution of daily rainfall (left hand ordinate) and expected change (right hand ordinate) for Hyderabad/India. 76

Figure 18. Flow accumulation map 77
Figure 19. Informal settlements detection algorithm and its calibration (for details see text) 79
Figure 20. Validation of slum detection algorithm (photo credit Martin Budde/PIK) 81
Figure 21. Vulnerability of informal settlements to floods 82
Figure 22. Screenshot of CATHY WebGIS (source: own work) 89

List of tables

Table 1. Satellite platforms commonly used in remote sensing of urban settlements (modified and enhanced after Patino and Duque 2013). 13
Table 2. Growth of slums and slum population in Hyderabad 27
Table 3. Results of principal component analysis 30
Table 4. Calculation of slum population densities 46
Table 5. Lacunarity values for binary images representing area which did not change between 2003 and 2010. 62
Table 6. Ground truthing 67

Abbreviations

MCH – Municipal Corporation of Hyderabad (covers 173 km^2 of the inner city area)

GHMC – Greater Hyderabad Municipal Corporation (covers 626 km^2 of extended urban area)

HUDA – Hyderabad Urban Development Authority (covers 1,348 km^2 of extended urban area)

HMDA – Hyderabad Metropolitan Development Authority (covers 7,100 km^2 of urban and adjacent rural area)

PPP – Purchasing Power Parity

Chapter I: Introduction

1. Urban world

The XXI century is the century of cities. The beginning of this century has been marked by the fact that more people worldwide were living in urban settlements than in rural areas (UN 2009). The role of cities is even more evident from the economic perspective, as urban areas contribute to over 80% of the global GDP (UN 2011b). Cities attract inhabitants because they concentrate human activity in one place, creating bundles of opportunities. While acting as concentrators and magnifiers, cities also suffer from a plethora of unresolved environmental and social problems.

The advantages of living in a city are of both a social and economic nature and include better access to goods and services, improved earning opportunities and lower dependency on the vicissitude of nature than staying in the countryside. The urbanisation process in many cities, particularly in the developing world, is driven both by the pull of cities and by the push from the misery of rural livelihood. Extreme poverty still remains a predominantly rural phenomenon worldwide, with some 75% of those who subsist on expenditures below PPP-adjusted $1-a-day still residing in rural areas in 2002, even when higher cost of living in urban areas is taken into account (Ferré et al. 2007).

In developing and newly industrialised countries the steady increase of the percentage of urban inhabitants has been accompanied by rapid population growth, producing an explosion-like picture. To put this into a perspective, the urban population in the developing world grew an average 1.2 million people per week between 2001 and 2011, or slightly less than one full year's demographic growth in Europe's urban areas (UN 2012). In Asia, the bulk of the increase in the number of urban dwellers is attributed to China and India. A predominant phenomenon of the developing world is the extensive growth of megacities – extremely large urban agglomerations which host more than 10 million inhabitants. By 2025, the UN expects 29 of the world's 37 megacities to be located in the developing world (UN 2009).

2. Urban slums

The growth of many cities in developing and newly industrialised countries is accompanied by the emergence of slums. The exact definition of a slum differs among countries and international organisations, but the general consensus is that slums are dilapidated and poverty-struck settlements which lack access to water, sanitation, electricity and land tenure.

The number of people living in slums of the world cities is highly disputed. Slums are very dynamic form of urban settlements and, being informal, are frequently stealthy to the eye of urban planners and alike. The latest UN reports estimate the number of people living in slums as close to 1 billion but, as pointed out by Carr-Hill (2013), the same number has been repeated since 2003, while no extensive urban redevelopment process has been observed that might cater for the growth in urban populations over the last decade. The calculations in UN reports use numbers provided by national governments. The authors of the report acknowledge substantial differences in methodology of slum population assessment and suggest cautious approach to the resulting data. Furthermore, the UN acknowledges the possibility of a data gap, noting that "Data collection and analysis on urban slums encounters a critical problem. Information is rarely disaggregated according to intra-urban location or socio-economic criteria. Thus, slum populations and the poorest squatters are statistically identical to middle class and wealthy urban dwellers. Worse, the poorest urban populations are often not included at all in data-gathering." (UN 2003).

Given the subcontinent's enormous population and widespread poverty, it is easy to expect that the largest slum population in the world is attributed to India. According to official figures this is true, and the 2011 Census of India reported the country to have a slum population of approximately 64 million people, with roughly half of all slums being 'notified', i.e. officially accepted by the government.

The rest populates either 'non-notified' slums that are known to the officials but lack formal slum status, or is completely invisible to the eye of a statistician. Giving India the due credit for putting a tremendous effort into locating and enumerating its slum dwellers, many researchers suspect the official national figures to contain a substantial error margin similar to the global ones. Accurate statistics are in fact difficult to come by, because poor and slum populations are often deliberately and sometimes massively under-counted by officials (Davis 2006). Agarwal (2011) questioned the accuracy of the slum population number on the grounds that the official statistics "do not include unaccounted for and unrecognized informal settlements and people residing in poor quality housing in inner city areas on construction sites, in urban fringe and on pavements".

3. Remote sensing of cities and slums

Short et al. (1996) characterised the data availability problem as 'the dirty little secret of world cities research'. While the application of new data acquisition methods such as high resolution remote sensing has enormously contributed to the improvement in the availability and quality of data, this observation still holds true for many cities in the developing world, and this is particularly visible in the domain of informal settlements.

Counting individual dwelling units is undoubtedly the most reliable method of slum population estimation. Although very accurate, this method is extremely time- and effort-intensive. On the other hand, remote sensing and advanced image processing methods have the potential to offer a worthy alternative to field data collection in certain situations. By virtue of its uniformity, satellite imagery is a useful tool to address the paucity of data on the morphology of cities, as it is capable to provide internally consistent and spatially homogeneous measurements of physical properties at considerably lower costs than in-situ measurements (Miller and Small 2003).

The relationship between the visual characteristics of the urban landscape and the socio-economic status of the population is a well established and active field of research. According to a recent state-of-the-art review (Patino and Duque 2013), detection of slums and deprivation hotspots as well as social vulnerability assessment is one of the major challenges to modern remote sensing in urban settings.

The earliest studies of urban places using airborne remotely sensed data were published in the Journal of Photogrammetric Engineering back in 1936 (Fugate et al. 2010). The space era brought the possibility to capture visual characteristics of large areas of the Earth surface, and the advance in sensor technology produced instruments with new spectral and spatial resolution capabilities. By the 1970s the spatial resolution of satellite-based sensors improved to a level that allowed identification of urban areas and later – distinguishing of urban features. This had brought the urban remote sensing science to a completely new level, as in order to be useful in urban morphology studies, satellite imagery had to be available at relatively high resolution levels. Specifically, to provide meaningful results, minimum spatial resolution of a satellite image should be one-half diameter of the smallest object of interest (Jensen and Cowen 1999). For an urban area, where the features of interest mostly consist of buildings and roads, this translates into the minimum spatial resolution of 0.25 - 0.5 m, with road centrelines detectable at resolutions of 1 to 30 m per pixel (Jensen and Cowen 1999). Until the end of XX century such sub-metre resolutions were limited to the domain of military intelligence operations. The situation changed in early 2000s, when IKONOS, QuickBird and OrbView platforms started to provide scientific community with very high resolution satellite imagery (Table 1).

Table 1. Satellite platforms commonly used in remote sensing of urban settlements (modified and enhanced after Patino and Duque 2013).

System	Spectral resolution	Spatial resolution (pixel size – metres)	Temporal resolution (days)	Archive since
Landsat MSS	3 bands visible 1 band infrared 1 band thermal	80	18	1972

System	Spectral resolution	Spatial resolution (pixel size – metres)	Temporal resolution (days)	Archive since
	infrared			
Landsat TM	3 bands visible 3 bands infrared 1 band thermal infrared	30 – visible and infrared 60 – thermal infrared	16	1986
Landsat ETM+	3 bands visible 3 bands infrared 2 bands thermal infrared 1 band panchromatic	30 – visible and infrared 60 – thermal infrared 15 – panchromatic	16	1999
SPOT 1 **SPOT 2** **SPOT 3**	2 bands visible 1 band infrared 1 Band panchromatic	20 – visible and infrared 10 – panchromatic	26	1986
SPOT 4	2 bands visible 2 band infrared 1 band panchromatic	20 – visible and infrared 10 – panchromatic	2-3	1998
SPOT 5	2 bands visible 2 bands infrared 1 band panchromatic	20 – mid infrared 10 – visible and near infrared 2.5–5 – panchromatic	2–3	2002
Ikonos	3 bands visible 1 band infrared	4 – multispectral 1 – panchromatic	1.5–2.9	1999
QuickBird	3 bands visible 1 band infrared 1 band panchromatic	2.4 – multispectral 0.6 – panchromatic	1–3.5	2001
WorldView-2	8 bands multispectral	1.85 – multispectral 0.46 –	1.1-3.7	2009

System	Spectral resolution	Spatial resolution (pixel size – metres)	Temporal resolution (days)	Archive since
	1 Band panchromatic	panchromatic		

High-resolution imagery can provide appropriate information to characterize the physical properties of an urban landscape. In particular, formal and informal neighbourhoods can be visibly delineated given sufficient spatial resolution because informal settlements often share unique spatial, structural, and contextual characteristics that distinguish them from other types of urban structures (e.g., formal residential, industrial, and commercial buildings), which can be detected and extracted from imagery (Graesser et al. 2012).

The history of satellite imagery-assisted slum identification together with advantages and drawbacks of methods used to date is presented in greater detail in the literature review sections of the respective papers in chapters II to IV.

4. Hyderabad

Hyderabad is the capital of Andhra Pradesh state in central South India. The population of Hyderabad metropolitan area has grown from 1 million inhabitants in 1951 to 7.7 million in 2011. The high-density built-up area of Hyderabad has grown from to 56 km^2 in 1989 to 240 km^2 in 2011 (Wakode et al. 2013). The urban agglomeration is expected to host 10-million inhabitants by around 2020, whereas the scenarios for the wider urban area project population size of 13 million in 2021 and 18 million in 2031 (HMDA 2011).

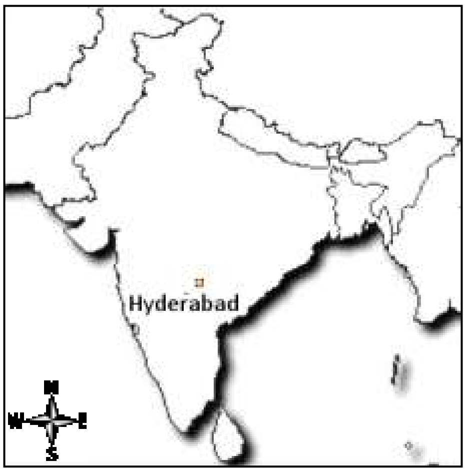


Figure 1. Location of Hyderabad in India.

Hyderabad is presently characterized by climatic conditions that are extreme in the sense of large variations in temperature and precipitation during different seasons.

Climate change calculations for the city, performed within the "Sustainable Hyderabad" show that these conditions are very likely to become more extreme in the future (Lüdeke et al. 2010). Already today, the city is hardly able to cope with these extremes. Climate change process has the potential to increase the frequency and amplitude of further damages. Nevertheless, a comprehensive assessment of the future impacts is missing, which is an obstacle for an efficient urban planning process.

While Hyderabad has substantially benefited from India's high-tech boom, up to a third of its population is believed to live in slums of various qualities (HMDA 2011). High prevalence of slums in the city is an undeniable fact, but unfortunately no coherent and plausible data on exact slum locations and slum population figures exist. Lack of reliable information on the state of slums in the city, augmented by very diverging views on the past and the future of slum development process create an atmosphere which neither supports sustainable urban planning, nor ensures adequate climate change impact assessment process. Many slums are often *terra incognita* to city's decision makers and the number and location of slums in Hyderabad, as well as the number of people residing in them differs among all the available data sources. The situation is further complicated by the fact that in many cases the designation of an area to a slum class is more related to political and economical benefits and not so much to the actual state of infrastructure or level of access to goods and services. Many of the areas considered to be slums by local authorities and subsequently reported as such by the census might have lost their slum nature (but not the slum status) over the years between their establishment and census data collection – an assumption which is supported by the results of a slum-based child labour survey in Hyderabad in 2007 (Centre for Good Governance 2008). This problem is not endemic to Hyderabad, but has been observed in many urban agglomerations in India and other newly industrialised and developing countries (Agarwal 2011; Satterthwaite 2010).

5. Rationale and research questions

The demand for unbiased slum location and population data and availability of high resolution satellite imagery has been the driving force behind this dissertation. The development of an automated remote sensing-based approach to slum identification in Hyderabad started as a part of an urban vulnerability study within the work package 1 “Potential climate change impacts and adaptation measures in Hyderabad” of the “Sustainable Hyderabad” project, which itself belongs to the constellation of projects within the “Megacities of Tomorrow” research programme, funded and managed by German Ministry of Education and Research. The downscaling of all 21 IPCC climate model results to Hyderabad indicated high probability of increase in frequency of heat waves and extreme precipitation events (> 80 mm/day) under A2 and B1 global emission scenarios (Lüdeke et al. 2010). An attempt to evaluate climate change-induced vulnerability and resilience of the city (Kit el at. 2011) struggled to acquire necessary socio-economic data for the city, and particularly – plausible and temporarily and spatially explicit data on slums and slum population in Hyderabad. Development of a satellite imagery-based slum identification method turned out to be the only appropriate way to acquire the necessary data and thus – to perform scientifically viable climate change vulnerability assessment.

This dissertation addresses the following research questions:

- Is it possible to automatically identify slums in an Indian megacity, exemplified by Hyderabad, using remote sensing data? Is lacunarity appropriate for this?
- Is it possible to use remote sensing data to assess the numbers of the people living in slums in Hyderabad and their spatial distribution? Can this improve the resolution of Census data and validate official slum population estimations?
- Is it possible to capture the dynamics of slum area change using multitemporal and multi-source satellite imagery? How to improve the robustness of the slum identification algorithm?

- What are the possible impacts of future climate conditions on slum population of Hyderabad? Is it possible to use the slum identification algorithm in vulnerability assessment?

The research questions listed above are addressed in detail in chapters II, III, IV and V. Chapter VI summarises the findings of this dissertation, highlights scientifically important results and outlines the direction for future work in this field.

This dissertation is structured as follows:

Chapter I: Introduction

Chapter II: Texture-based identification of urban slums in Hyderabad, India using remote sensing data
Published as: Kit O, Lüdeke MKB, Reckien D (2012): Texture-based identification of urban slums in Hyderabad, India using remote sensing data. *Applied Geography* 32 (2): 660-667.

Chapter III: Satellite imagery-assisted slum population assessment in Hyderabad/ India
Published as: Kit O, Lüdeke MKB, Reckien D (2013): Defining the bull's eye: satellite imagery-assisted slum population assessment in Hyderabad/India. *Urban Geography* 34 (3): 413-424.

Chapter IV: Automated detection of slum area change in Hyderabad, India using multitemporal satellite imagery
Published as: Kit O, Lüdeke MKB (2013): Automated detection of slum area change in Hyderabad, India using multitemporal satellite imagery. *ISPRS Journal of Photogrammetry and Remote Sensing* 83: 130-137.

Chapter V: Assessment of climate change-induced vulnerability to floods in Hyderabad/India using remote sensing data

Published as: Kit O, Lüdeke MKB, Reckien D (2011): Assessment of climate change-induced vulnerability to floods in Hyderabad/India using remote sensing data. In: Otto-Zimmermann, K. (Ed.), *Resilient Cities - Cities and Adaptation to Climate Change, Local Sustainability*, 1(2), 35-44.

Chapter VI: Results and conclusions

Chapters II, III and IV are standalone peer-reviewed papers published in ISI-indexed journals and fulfil the formal requirements to a cumulative doctoral dissertation set by the Department of Geography of Humboldt University of Berlin. Chapter V is a peer-reviewed chapter in a book published by Springer Science+Business Media B.V. Due to the nature of a cumulative dissertation, which incorporates unchanged original research papers, a certain amount of recurrence in this thesis is unavoidable.

Chapter II:

Texture-based identification of urban slums in Hyderabad, India using remote sensing data

Applied Geography 32 (2): 660-667.

Oleksandr Kit, Matthias Lüdeke and Diana Reckien

© 2012 Elsevier Ltd. All rights reserved.

doi:10.1016/j.apgeog.2011.07.016

Received 31 March 2011; revised 30 July 2011;

accepted 31 July 20011.

Abstract

Slums are highly dynamic forms of urban fabric, whose development seldom follows rules and guidelines imposed by city administration. The vast majority of slums are located in the developing world, where the decision makers often lack the resources to track their spread. This paper outlines a methodology to identify informal settlements out of high resolution satellite imagery using the concept of lacunarity. Principal component analysis and line detection algorithms were applied alternatively to obtain a high resolution binary representation of the city of Hyderabad, India and used to calculate lacunarity values over a 60x60 metre grid. A number of ground truthing areas were used to classify the resulting datasets and to identify lacunarity ranges which are typical for settlement types that combine high density housing and small dwelling size – features characteristic for urban slums in India. It was discovered that the line detection algorithm is advantageous over principal component analysis in providing suitable binary datasets for lacunarity analysis as it is less sensitive to spectral variability within mosaicked imagery. The resulting slum location map constitutes an efficient tool in identifying particularly overcrowded areas of the city and can be used as a reliable source in vulnerability and resilience assessments at a later stage. The proposed methodology allows for rapid analysis and comparison of multi-temporal data and can be applied on many developing urban agglomerations around the world.

1. Introduction

The rapid advance of urbanisation throughout the world has caused the first ever prevalence of the number of people living in urban settlements than in rural ones (UN 2009), an increase of 10% or approximately 500 million people from 1990. This phenomenon essentially marks a new stage in the pace of urban development. Such a high rate of urbanisation is often unaccompanied by adequate development of infrastructure, be it housing, transport or utility grids, particularly in the developing world, where most of the urbanisation takes place. Together with the

large share of informal low-paid employment, this process extraordinarily contributes to the growth of informal settlements (UN 2009).
Generally, urbanisation can lead to both, the growth of informal as well as formal urban settlements, of low-, medium- and potentially upper class housing. 'Slum' has become a term to uniformly refer to the large variety of high-density, vastly developing, lower class residential areas with small dwelling unit sizes found in the cities of the developing world, although no common definition across countries exists and some countries lack a definition at all.

The UN Data Glossary (UN 2011a) attempts a common definition but remains rather broad by defining slums as "areas of older housing that are deteriorating in the sense of their being underserviced, overcrowded and dilapidated", whereas the UN HABITAT (UN 2006) defines slums as households that "lack any one of the following five elements:

1. durability of housing (permanent and adequate structure in non-hazardous location),
2. sufficient living area (not more than two people sharing the same room),
3. access to improved water (access to sufficient amount of water for family use, at an affordable price, available to household members without being subject to extreme effort),
4. access to improved sanitation (access to an excreta disposal system, either in the form of a private toilet or a public toilet shared with a reasonable number of people),
5. security of tenure (evidence of documentation to prove secure tenure status or de facto or perceived protection from evictions).

The UN provides general updates on the issue in its "State of the World's Cities Reports", and UN HABITAT dedicated a whole volume to the challenge of slums in 2003 (UN 2003). More recent estimates give a slum population of about 16% of the world's population (UN 2009), with India officially scoring below average with 6% slum population (Government of India 2010c) despite the fact that the UN HABITAT definition is stricter than the one applied in India.

In India, slums can be either formally approved by the city authority or informally sprout. The designation of a residential area as a slum comes with a certain degree of security and access to facilities, and is necessary to benefit from government services and basic infrastructure in return. Slums normally start as informal settlements and are eventually approved after a long time of informal existence. Following definitions of slum areas are used in India:

1. All specified areas in a town or city notified as 'Slum' by state/local government and UT Administration under any Act including the 'Slum Act'.
2. All areas recognized as 'Slum' by state/local government and UT Administration, Housing and Slum Boards, which may have not been formally notified as slum under any act;
3. A compact area of at least 300 population or about 60-70 households of poorly built congested tenements, in unhygienic environment usually with inadequate infrastructure and lacking in proper sanitary and drinking water facilities (Census of India 2001a).

Slums in India are additionally categorized by their building type, which is described as (semi-) pucca or (semi-) kutcha. Pucca refers to houses of more permanent building materials, such as burned bricks, stones, asbestos cement sheets, (corrugated) metal plates and other roof tiles, whereas kutcha describes the use of non-permanent building materials, for example, clay, wood, bamboo, leaves or carton. Pucca houses can have more than one storey and always show a flat roof, while kutcha houses are one storey only and often resemble tents (The Community Studies Team 2007; Baltsavias and Mason 1997).

India aims to be slum-free by 2014 (Government of India 2010c) and in so trying, amongst other initiatives, launched an extensive government scheme of 12.7 billion Indian Rupees (INR) (USD 278 million), the Rajiv Awas Yojana. However, recent forecasts to the socio-economic development of Indian cities uniformly estimate that slums will remain one of India's urban features well into the future (UN 2009).

For obvious reasons, a slum detection algorithm which is based on satellite imagery alone is not capable of considering such properties of a slum as land tenure or service provision. Nevertheless, since it is generally accepted that housing size and density are distinctive properties of a slum (Niebergall et al. 2008), it is appropriate to rely on the internal building structure of a slum in the methodology development process.

Reliable identification of slums and tracking of their growth has always been a difficult task for urban administrators in the developing world. As the alternatively used term 'informal settlement' suggests, such developments are, particularly in the early stages, not necessarily reported to the authorities and therefore lack proper referencing in land property registers or urban development plans. The need to know past and future locations of slums arises from the responsibility of a government to provide for its citizens, which can be narrowed down to the identification of the groups in need, development of housing, employment and service provision policies as well as risk reduction measures. While such information might be available on the lowest levels of India’s city structure (colonies and wards), the imperfect vertical communication often leads to situations when municipalities and municipal corporations cannot appropriately describe fine spatial and socio-economical structure of the areas they manage, which is vitally important for adequate steering of the city growth. The reliance on the 1994 slum location data in the 2010 Master Plan for Hyderabad is an eminent indicator of the necessity of our research, which aims to provide local and regional planning authorities with a tool, capable of identifying slums through the use of recent high-resolution satellite imagery. Therefore, new methodologies and tools as well as techniques and policies are required to monitor urban growth and alteration across the megacity and to forecast areas of risk – all within shorter time frames and at a larger scale than previously accepted (Herold et al. 2003). This will support a more proactive and sustainable urban planning and land management (UN 2003).

The ascent of increasingly high resolution sensors aboard earth-orbiting civil satellites has created spatiotemporally continuous and politically less biased sources of data about the surface of our planet. While first uses of remote sensing data for land use classification were confined to large-scale cartographic and agricultural studies (Lillesand 1990), the 1970s also saw the initial use of satellite imagery in urban research (Ellefsen et al. 1973; Lo and Welch 1977). Some 40 years later, urban planning and administration in megacities is becoming unthinkable without the use of information derived from remote sensing platforms (Maktave et al. 2005). For example, the mere land use classification of built-up and non-built-up areas performed during the urban expansion of Greater Dhaka, Bangladesh, has produced important insights into the spatial patterns of the city's expansion (Dewan and Yamaguchi 2009).

Accurate detection and classification of informal settlements using remote sensing data pose real challenges to researchers and decision-makers alike. Unlike agricultural land or other natural vegetation types, urban structures lack unique and easily distinguishable spectral signatures. Even to a first approximation cities are not spatially uniform bodies but constitute a collection of discrete objects, be it streets, houses or green spaces. This is particularly evident in slums where the variety of materials used for roof construction is so great (Baltsavias and Mason 1997) that it effectively prohibits any attempt of urban fabric classification based on spectral properties alone. On the other hand, internal spatial characteristics of slums such as housing density, size and structure of individual dwelling units emerge as promising and efficient methods of slum detection.

Baud et al. (2010) successfully merged local knowledge with an indicator-based visual interpretation technique to extract different classes of residential areas matching administrative settlement categories (formal/informal) using high resolution satellite imagery of Delhi/India. The approach, however, extensively relies on manual image processing and is thus of limited use in operational monitoring circumstances where limited human resources and time frames are available for processing of multitemporal datasets. Nevertheless, visual interpretation is still frequently used for visual checking and evaluation of classification carried out by other means (Hurskainen and Pellikka 2004).

The growing availability of computing power as well as a the need to continuously track land use change within large and often nebulous spatial boundaries have created a need for rapid slum identification which does not allow for extensive but time-consuming fieldwork. This is the area where fully automated methods start to play an increasingly important role. While summarising challenges and achievements of object detection using multi-scale satellite imagery, Blaschke (2010) stresses the importance of automated object detection in object-based image analysis as the approach becomes increasingly used in planning and decision-support workflows. Object-based analysis of very high resolution imagery is proven to provide consistently better results than per-pixel classification, particularly in parts of a city characterised by low spectral separability of urban features (Bhaskaran et al. 2010).

Aiming to identify slums in Hyderabad, we consider cities to be complex systems composed of non-linear and multiple scale iterations of spatial and physical heterogeneous components (Amorim et al. 2009). Hence, they can be analysed by the means of fractal mathematics. Several authors (Amorim et al. 2009; Barros Filho and Sobreira 2008; Myint and Lam, 2005) successfully used lacunarity as a measure of surface texture to classify urban settlements and to detect different housing types within city boundaries. It was Gefen et al. (1983) who defined lacunarity as a measure of the deviation of a geometric object, such as a fractal, from translational invariance, being a suitable indicator to measure spatial heterogeneity. Since lacunarity values represent the distribution of gaps within an image at various scales, it is considered to be a suitable and promising tool, capable of assessing urban structure and isolate distinctive morphological features.

The main focus of this paper is to identify the locations of slums in Hyderabad/India aiming to be useful to urban decision makers. We therefore explore the extent to which remote sensing data and advanced image processing techniques can be applied to identify slums with minimal operator intervention.
Specifically, the following objectives are addressed:

1. Identify slums in Hyderabad/India using very high resolution satellite imagery;
2. Test the methodology of slum identification which is based on the lacunarity algorithm

3. Compare the performance between principal component analysis and line detection algorithms in production of suitable binary datasets for the following lacunarity computation.

2. Study area

Hyderabad is the capital of Andhra Pradesh state in central South India. It grew from about 1 million inhabitants in 1951 to about 7 million in 2001. It is characterised by growth rates of more than 50% during 1981-91 and of 27% during 1991-2001(GHMC 2010). The urban agglomeration is expected to host 10-million inhabitants by around 2020, whereas the scenarios for the wider urban area (HUDA area as per MCH 2005) project a crossing of the 10 million mark by 2015.

Hyderabad is a city that benefited substantially from India's high-tech boom, with the majority of the GDP generated in the information technology, pharmaceutical and chemical industries. Just like many other emerging megacities, Hyderabad suffers from significant social inequalities; more than a third of its population is believed to live in slums of various qualities (HMDA 2011). The latest available data on slum growth is summarized in Table 2:

Table 2. Growth of slums and slum population in Hyderabad

Year	**No. of slums**	**Slum population, thousands**	**City population, thousands**	**% of total population**	**Annual growth rate**
1962	106	120	1 233	9.73	
1967	194	168			
1972	282	300	1 732	17.32	9.6
1976	300	320			
1978	377	400			
1979	455	408			

Year	No. of slums	Slum population, thousands	City population, thousands	% of total population	Annual growth rate
1981	470	540	2 251	23.99	6.75
1986	662	859			
1994	811	1 258	3 298	38.14	6.72
2001*		601	3 454	17.4	
2001†	1142	1411	3 633	38.83	

**According to the MCH*

†According to the Government of India

(Sources: Hyderabad Concept Plan, MCH and Master Plan for Hyderabad Metropolitan Area by HUDA 2003, as quoted by HMDA 2010; MCH 2005; Census of India 2001b)

The disagreement of official sources on the slum population in 2001 can be possibly explained by use of different slum notification data. The notification process is complicated and sometimes lengthy, in which the community needs to prove certain characteristics listed in the Andhra Pradesh Official Slum Act of 1956 (Naidu 1990). As the notification is also a political process, the inhabitants of recently formed settlements, particularly poor and dilapidated areas, and former rural migrants often lack the necessary political lobbying.

Given the large proportion of the population of the city living in slums, it is remarkably distressing that the assessment and monitoring of slums in Hyderabad is performed on a rather ad-hoc basis, with results that vary significantly among different government agencies. However, one should not forget that the notification of slums comes with a certain responsibility of the authority to provide for basic services. Therefore the publication of slum statistics as well as the development of a slum detection algorithm has a certain political notion.

3. Methodology

3.1. Data source

Very high resolution imagery from the QuickBird satellite was used as a source of remote sensing data. The QuickBird sensor collects multispectral and panchromatic imagery concurrently, with resolutions of 2.44–2.88 m and 0.61–0.72 m, respectively, depending upon the off-nadir viewing angle (0–25 degrees) (Cheng et al. 2003). The imagery used in this study was delivered by the data provider as a gridded dataset which was radiometrically calibrated, pan-sharpened, corrected for sensor- and platform-induced distortions and mapped to a UTM projection zone 44N. The data covers 400 km^2 of urban territory within a rectangular bounding box of 78°22'-34' east longitude and 17°18'-30' north latitude.

3.2. Data preparation

The lacunarity calculation algorithm works best with binary data which is represented as a matrix holding 0 (no housing) and 1 (housing) values (Malhi and Román-Cuesta 2008). At a sufficiently fine resolution such a matrix is capable of representing the internal structure of slums as a grid of dwelling units and open space between them.

Since there is no universally accepted procedure of obtaining binary datasets for lacunarity calculations out of pan-sharpened satellite imagery, two different binarisation methods were used and compared: PCA- and line detection-based.

Method 1 combined principal component analysis and threshold binarisation. Since urban zones are characterized by generally higher internal variability than the non-urban ones (Weizman and Goldberger 2009), principal component analysis (PCA) seems to be an appropriate technique which can be used to reduce the dimensionality of the data. A study by Muchoney and Haack (1994) found PCA superior to an unsupervised classification of composite imagery and hence more appropriate for an automated feature detection procedure.

Method 2 is based on the assumption that while the housing structure within informal settlements in India does not normally follow any regular pattern (Baud et al. 2010), the edges between a dwelling unit and the surrounding area (open space, streets and paths) are still distinguishable. Therefore, it is appropriate to apply a line detection algorithm as implemented in VIPS (Martinez and Cupitt 2005) and to create a binary matrix suitable for the lacunarity calculation by this method. Both methods are described in more detail hereafter.

3.2.1 Method 1 (PCA-based)

Original multispectral imagery was imported into GRASS GIS, split into red, green and blue colour channels and analysed using the *i.pca* method (Richards and Jia 2006). The process took approximately 30 hours on a laptop computer (peak performance 10 Gflops) and resulted in the distribution of eigenvalues as per Table 3.

Table 3. Results of principal component analysis

Component	Eigenvalue	Vector	Importance
1	46167.55	-0.5476,-0.6050,-0.5780	99.29%
2	286.40	0.6285, 0.1586,-0.7615	0.62%
3	45.67	0.5524,-0.7803, 0.2934	0.10%

The extremely high importance of the first component let us use it as an appropriate unidimensional representation of the RGB colour space of the satellite image. The first component matrix was stretched to a range of 0…255 and then converted into binary matrix using the VIPS binarisation function (Martinez and Cupitt 2005), setting black/white threshold to 127. This turns pixels having spectral value lower than 127 (exactly in the middle of the value diapason) into white and those higher than 127 into black, respectively, producing the binary matrix *pca_127*. In order to identify the most suitable threshold, binary matrices are created using 120 and 130 as splitting points, producing binary matrices *pca_120* and *pca_130*. Figure 2 presents a sample result of the binarisation process.

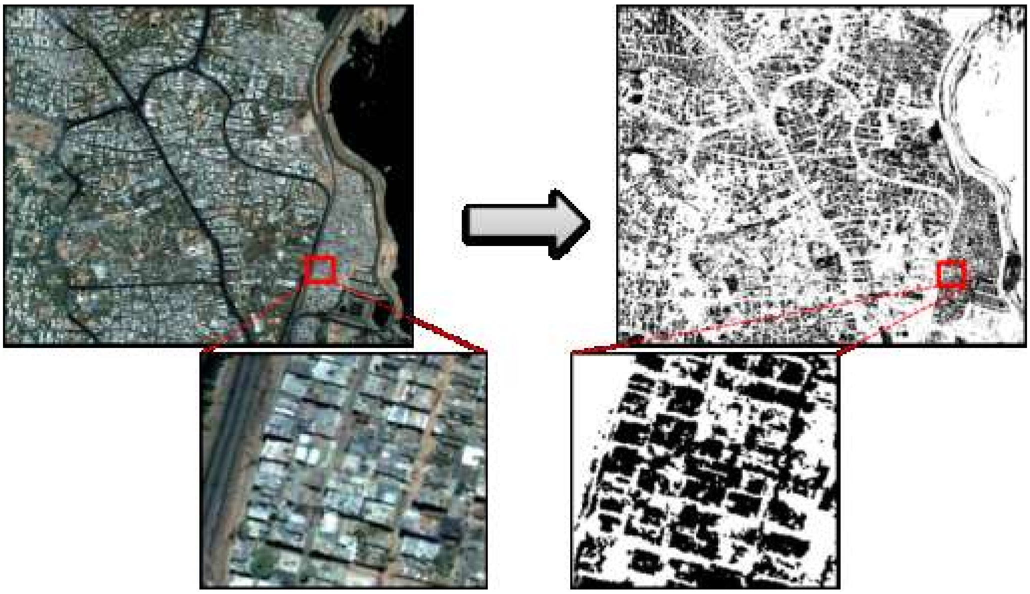


Figure 2. Sample natural colour image and binary matrix pca_127 (both covering Punjagutta area of Hyderabad)

3.2.2 Method 2 (Line detection-based)

Original multispectral image was converted into a panchromatic line matrix using the im_lindetect function as defined by Martinez and Cupitt (2005). In order to produce binary matrices comparable to those used by method 1, different binary threshold values had to be chosen. Those were empirically set at 60, 70 and 80, obtaining binary matrices *line_60*, *line_70* and *line_80* respectively. This method has produced three binary datasets, the extract from one of them is visualised by Figure 3.

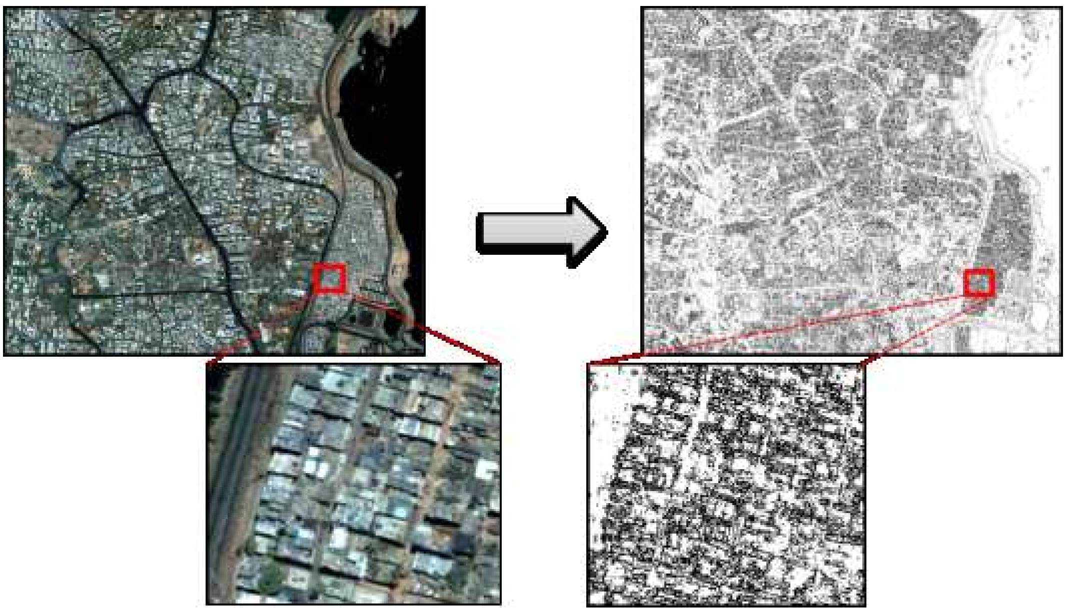


Figure 3. Sample natural colour image and binary matrix line_70 (both covering Punjagutta area of Hyderabad)

3.3. *Lacunarity calculation*

Lacunarity was computed using the algorithm provided by Malhi and Román-Cuesta (2008), where lacunarity Λ of a subset P is defined as:

$$\Lambda_P = \sigma_r \Big/ \bar{x}_r^2 + 1$$

where σ_r is the variance and $\bar{x}_r$ is the arithmetic mean of the number of filled pixels within all r-sized unique square subsets (referred to as sampling window) of the larger subset P of the original binary image. As the sampling window of size r traverses through P, the number of filled pixels within every position of this window is counted and stored in an array. After all unique sampling window positions are processed the algorithm calculates variance σ and arithmetical mean $\bar{x}$ for P and then computes a single lacunarity value Λ for this subset.

The algorithm produces a rectangular matrix holding decimal lacunarity values, which is stored as a flat GeoTIFF image. Since the georeferencing parameters of the original imagery have been known, it was possible to georeference the lacunarity matrix by producing ESRI world files.

According to Malhi and Román-Cuesta (2008), the floating window should be big enough to cover the largest units of interest (that is a dwelling unit in our case), but do not exceed the size which makes it possible to reveal finer-scale information on variation in the image. As typical dwelling units in slums rarely exceed several metres in any dimension and gaps between houses are expressed in fractions of a metre rather than in whole metres, the size of floating window was kept comparatively small, being set in three runs at 5, 10 and 15 px (3, 6 and 9 m respectively). This takes into account the findings of Niebergall et al. (2008), who stated that high building density and small building size are the most important characteristics for identifying informal settlements from very high resolution image data.

A Python routine was developed to perform the calculations, which took approximately 20 hours on a laptop computer (peak performance 10 Gflops) despite the extensive use of Numeric Python and Scientific Python fast computation techniques.

4. Results

Using three different binarisation thresholds and floating window sizes, both algorithms have produced 18 considerably distinct lacunarity matrices for the whole of Hyderabad (9 each).

To decide which of these parameterisations and choice of the binarisation algorithm yield the best results, these 18 matrices were compared with several subsets of the original satellite image where settlement structure was identified by ground truthing surveys during research stays in Hyderabad in autumn 2009 and winter 2010. Using this data, an area in the central part of the city was selected and classified as a slum/non-slum matrix (box SLUM in Figure 4). This matrix was then compared to computed lacunarity results and used to calculate identification confidence for each binarisation threshold and floating window size. The bottom part of the Figure 4 contains the resulting charts that plot slum identification probability against lacunarity and describe three lacunarity ranges:

- < 1.1: very strong signal, the probability of a cell not being a slum heads to 100%.
- to 1.15: strong signal, the probability of a cell being a slum is high;
- 1.15: very strong signal, the probability of a cell not being a slum heads to 100%.

The calibration results indicate that a line detection algorithm delivers consistently better results than principal component analysis and is particularly good at a 10 pixel floating window size and 60 binarisation threshold. This combination of parameters suggests that the highest correlation between calculated and observed slum locations occurs at lacunarity values 1.10 to 1.15, with identification probability reaching 83.33%. This agrees with findings of Malhi and Román-Cuesta (2008), stating that lower lacunarity values refer to denser settlement and hence higher slum probability. The size of the optimal floating window is also consistent with our initial assumption that average dwelling unit size in slums falls into 3 to 6 m bracket.

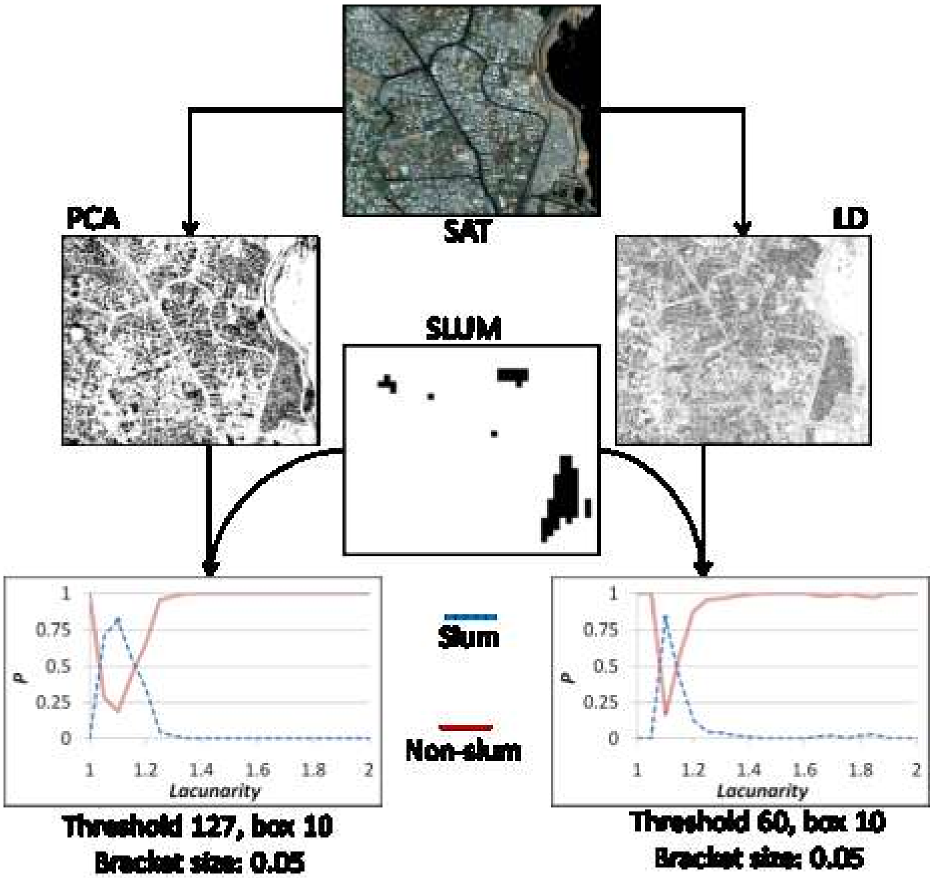


Figure 4. Slum detection flowchart.

In order to test the accuracy of the chosen approach the method was validated by the means of analysis of different subsets of the QuickBird scene covering other parts of the city which were also studied during ground truthing visits. The algorithm has identified several areas within the subset where lacunarity values fluctuated between 1.10 and 1.15. The georeferenced street-level photographs taken both in these areas and outside them show substantial differences in housing types and generally support slum/non-slum classification made by the slum detection algorithm. Figure 5 summarises the results of the algorithm validation procedure and shows two different subsets of the original satellite image together with georeferenced photographs taken during field surveys.

Figure 5. Slum Locations in Hyderabad (red areas) and georeferenced field photographs of Rasolpoora slum in the northern and Nagamiah Kunta slum in the eastern part of the city (photo credit: Martin Budde/PIK)

5. Discussion

The sub-metre satellite imagery appears to be a suitable data source for identification of slums in Hyderabad using advanced image analysis techniques. While the resolution might be sufficient for manual image processing (e.g. Baud et al. 2010), such an approach would be of little use in operational monitoring circumstances under limited availability of time and human resources. The specific spatial structure of slums in terms of object density and heterogeneity suggests the use of lacunarity as a measure of surface texture for their detection. The lacunarity matrix computed for the city of Hyderabad contains a number of records which fall into 1.10 to 1.15 range – a value bracket which covers the overwhelming majority of slums within the calibration subset. This interval is also supported by Malhi and

Román-Cuesta (2008), who state that lower lacunarity values refer to denser settlements and hence to higher slum probability. The street-level photography of additional validation areas confirms the presence of slums in the areas characterised by lacunarity values 1.10 to 1.15 as well.

Further visual comparison of the lacunarity map and satellite image has shown, however, that approximately 10% of cells with lacunarity values lying in range 1.10 to 1.15 were placed over the parts of the city which clearly contained no slums. Such areas included water bodies and some green spaces – areas, whose binary signatures might have resembled those of a slum in terms of feature density and structure. Due to their distinctive spectral signatures, water bodies and green spaces can be reliably identified and masked by an unsupervised imagery clustering procedure, which has recently been found to be able to deliver sufficient accuracy for studies where the collection of representative signatures is not feasible or the terrain being mapped is particularly heterogeneous (Rozenstein and Karnieli, 2011). This approach is already earmarked for use in future research and has great potential to further improve slum detection quality, at the same time eliminating the majority of erroneously classified cells.

The performance of the lacunarity-based slum detection algorithm greatly depends on the technique used to prepare binary datasets used in the calculation. It has been observed that the calibration dataset correlates better to the lacunarity matrix computed using line detection-based binary source that to the PCA-based one. We assume that this is caused by the fact that line detection routine as implemented by Martinez and Cupitt (2005), already pre-outlines individual objects within the satellite image and hence creates a more suitable environment for the lacunarity algorithm to work in.

This work acknowledges the fact that lacunarity is an aggregate function and as such produces raster grids with one cell representing the spatial heterogeneity within a certain matrix. Given the 60-cm scale of satellite imagery, typical 100 × 100 pixel matrix translates into 3600 m^2 square polygons. Since the boundaries of informal settlements seldom correspond to lacunarity grid cells, the method can potentially misplace or misidentify slums covering smaller areas. Hence, the method performs best in identifying slums larger than 3600 m^2 threshold.

More generally, the use of lacunarity-based slum identification in urban decision making addresses the responsibility of the authority to provide for all citizens it serves, irrespective from their social class or living area. The ability to rapidly detect slums using high resolution imagery hence creates an opportunity to address new developments in the city in a timely and appropriate manner.

6. Summary and conclusions

Sustainable urban planning and management require land use data which reliably represent the urban fabric at any point in time up to the present. We have suggested a technique for detection of urban slums using remote sensing data and lacunarity-based pattern recognition. The methodology is capable of rapidly creating a coherent dataset describing the majority of informal settlements in the city of Hyderabad irrespective of technical (lighting conditions, season, and manpower availability) and political limitations. The resulting map agrees with the scattered body of knowledge on slum locations in various areas in the city, such as Rasolpoora slum near the military airport, slum fields around industrial estates of Patancheru in the north-west of the city, the high density of informal settlements within unclaimed land on the banks of drainage channels.

The methodology outlined in this paper will be used in subsequent studies looking at the dynamics of slum growth in Hyderabad by analysing multi-temporal very high resolution imagery. The resulting map of informal areas will also be used to assess the degree of vulnerability to climate change-induced extreme weather events and to ultimately suggest the most important adaptation measures. Since the method makes use of generalised urban morphology rather than specifically local features, it has the potential for successful use in other cities in developing world. The fact that no proprietary software is being used in the whole image processing and slum identification process makes the methodology particularly suitable to be used in cities with limited resources.

This paper presented an algorithm which is verified to be capable of identifying slums in Hyderabad (India) using very high resolution remote sensing data. We found that slums in Hyderabad occupied a total area of 6.4 km^2 or approximately 1.6% of the total area in 2003. Slums are high density settlements, with a typical average urban population density of 22,000 persons/km^2 for India (Baud et al. 2009). 6.4 km^2 of slum can hence host up to 140,000 slum dwellers. The majority of identified slums in Hyderabad were located on the edge of the city, particularly near the industrial areas of Patancheru and Secunderabad.

While the identified slum population figures for Hyderabad are significantly lower than the official data (see Table 2), it should be noted that the outlined methodology does only rely on the structural characteristics of a slum and the results cannot be directly compared to the much broader and often politically biased definition of a slum in India. Slums are very dynamic and often patchy forms of urban fabric which frequently undergo slum upgrading processes. The lacunarity algorithm is hence capable of identifying the core of a slum, the very area with particularly dense and jammed housing that is particularly vulnerable to natural and socio-economic hazards. The advantage of this approach is that it gives urban managers the option to increase the efficiency of their often very limited resources and to target support and improvement measures at those particularly in need. The relatively low hardware requirements and absence of software licensing costs also make the technique feasible for use in developing countries.

We expect the lacunarity algorithm to be capable to identify slums in other areas of the world and invite researchers working in the field to collaboration.

7. Acknowledgements

The authors acknowledge financial support from the Federal Ministry of Education and Research of Germany (BMBF) under the project “Future Megacities”.

Chapter III:

Defining the bull's eye: satellite imagery-assisted slum population assessment in Hyderabad/India

Urban Geography 34 (3): 413-424.

Oleksandr Kit, Matthias Lüdeke and Diana Reckien

© 2013 Taylor & Francis. All rights reserved.

doi: 10.1080/02723638.2013.778665

Received 15 February 2012; revised 16 July 2012;

accepted 24 October 2012.

Abstract

This paper presents an approach to qualitative and spatial assessment of slum population numbers in Hyderabad, India using circle-based population data from the Census of India and results of the analysis of high resolution QuickBird satellite image data (2003) derived from automatic line detection and lacunarity algorithm. This approach provides plausible and spatially explicit aggregate statistics of slum population numbers within the city. This work suggests that both over- and underreporting of slum population numbers does occur in Hyderabad, and provides an improved view on the slum distribution patterns within this urban agglomeration.

1. Introduction

In 2012, slums remain a distinct feature of many large urban agglomerations in developing and newly industrialized countries. Despite the wide range of slum definitions across countries and international organisations, it is generally accepted that highly crowded, underserviced and dilapidated settlements (UN 2011a) are currently home to approximately 828 million people (UN 2012).

Notwithstanding the noteworthy efforts and strong political will of local and national governments, slums remain an integral part of the urban landscape in India. The official figures suggest 22% of the total urban population of India and, more specifically, 35% of the population of the city of Hyderabad lives in slums (Census of India 2001).

In its 2010 report, the India's Committee on Slums Statistics suggested a definition of a slum which differs from the one adopted by the 2001 Census of India, describing it as "a compact settlement of at least 20 households with a collection of poorly built tenements, mostly of temporary nature, crowded together usually with inadequate sanitary and drinking water facilities in unhygienic conditions" (Government of India 2010c). This report also stresses the acute need for a reliable slum database and expects the total slum population of India to exceed 100 million mark by 2015.

According to Satterthwaite (2010), many national sample surveys potentially under-represent populations living in informal settlements. This is partially caused by the fact that the process of cataloguing and administrative recognition of slums is led by respective municipalities, corporations, local bodies or development authorities, which either assign the slum status to certain parts of the city (naming them "notified slum"), or not, using a frequently untransparent, subjective or misleading set of criteria (Risbud 2010). This process established the term "non-notified slum" – an area, which is a slum *de facto* but not *de jure*. This claim is supported by Agarwal (2011), who notes that the official statistics on the slum population in urban areas of India tend to be inaccurate, because a large proportion of low income urban clusters are informal and are not classified as "slums" or "notified slums". Furthermore, substantial differences between slum population numbers reported by the Census of India and by local municipal corporations (including the Municipal Corporation of Hyderabad – MCH) were identified by Risbud (2010).

The 65th National Sample Survey (2008-2009) concludes that approximately a quarter of all slums in Andhra Pradesh are non-notified ones (Government of India 2010b). The survey carried out by the Centre for Good Governance in 2008 stumbled upon a problem that 146 slums from the slum list provided by the Municipal Corporation of Hyderabad did not exist at the time of survey. Furthermore, 21 slums were replaced by multi-level apartments, shopping centres etc (Centre for Good Governance 2008).

The non-planned and frequently informal and non-notified nature of slums in Hyderabad seems to fit into the modern, agile urban planning framework adopted by India's metropolitan cities as a consequence of the transition from rigid, impracticable and non-implementable Master Plans to flexible vision documents such as City Development Plans (Kundu 2011). This, however, does not relieve city administrators of their duties to provide basic public services for all population strata. Lacking or incorrect slum distribution information potentially adds to the strain on public services budget and potentially undermines fair and efficient resource allocation. Therefore, reasonably accurate and timely estimation of numbers and spatial distribution pattern of slum populations in the city will remain an important task well into the future.

Counting individual dwelling units is undoubtedly the most reliable method of slum population estimation. Although very accurate, this method is extremely time- and effort-intensive. On the other hand, remote sensing and advanced image processing methods have the potential to offer a worthy alternative to field data collection in certain situations. By virtue of its uniformity, satellite imagery is a useful tool to address the paucity of data on urban populations.

Almeida et al. (2010) proposed a method to estimate the population of the informal settlements of Rio de Janeiro, Brazil, using Ikonos high resolution satellite imagery and object-based image analysis. However, this method is limited to settlements consisting of multi-storey residential buildings and is therefore not applicable to single- or two-storey slums of Hyderabad. Baud et al. (2010) successfully used an indicator-based visual interpretation technique to identify sub-standard residential areas of Delhi, India, from Ikonos scenes, but neither covered a substantial number of wards in the city nor attempted to calculate the slum population within those wards. Nolte (2010) relied on the normalised difference vegetation index (NDVI) computed from QuickBird and Landsat imagery to identify built-up area of Ahmedabad, India, and to model the population distribution in the city, but she did not distinguish between the slum/non-slum land use classifications behind the data provided by the Census of India 2001. QuickBird imagery and object-based classification approach are a superior source of information for satellite imagery-assisted urban demography and particularly urban slum study (Stoler et al. 2012).

The main focus of this paper is to quantitatively assess the numbers and spatial distribution pattern of slum population in Hyderabad, India. This work advances the concept of satellite imagery-assisted slum identification presented by authors' previous work in this field (Kit et al. 2012) by making a step towards assessment of the numbers of slum dwellers within each of Hyderabad's circle- and ward-level administrative units. This paper compares slum population figures obtained through the lacunarity-based slum identification method to official figures and attempts to explain the difference both in numbers and in spatial distribution of slum population. Additionally, we aim to produce seamless aggregate slum population numbers for the area administered by the Municipal Corporation of Hyderabad (MCH) at much finer spatial scale than normally reported by the authorities, namely wards instead of circles.

2. Study area

Hyderabad is the capital of Andhra Pradesh state in central South India. It grew from about one million inhabitants in 1951 to about seven million in 2001. It is characterised by population growth rates of more than 50% during 1981-91 and of 27% during 1991-2001 (GHMC 2010). The urban agglomeration is expected to host 10-million inhabitants by around 2020, whereas the scenarios for the wider Hyderabad Urban Development Authority area reach the 10 million mark by 2015 (MCH 2005).

Figure 6. Location of Hyderabad in India

3. Methodology

Aiming to identify slums in Hyderabad, we consider cities to be complex systems composed of non-linear and multiple scale iterations of heterogeneous spatial and physical components (Amorim et al. 2009). The starting point of our analysis is the relation between the lacunarity value of a 60m × 60m image of an urban subarea and the probability that this subarea is morphologically similar to a slum. Lacunarity is a measure of spatial heterogeneity that identifies the granularity of the visible urban structure. It is sensitive to quasi-regularly repeated small objects and an elaboration of structural measures like the fractal dimension (Amorim et al. 2009). Lacunarity is calculated from a QuickBird satellite panchromatic image (spatial resolution 0.6 m × 0.6 m) comprising of 100 × 100 image pixels for each subarea analysed. Two important parameters to be determined in advance are the size of the subarea and the size of a sliding window which runs over the whole subarea thereby counting the "gaps" (lacunae) for each window position. The size of the window has to reflect the typical scales of houses, paths and non-built up areas in slums while the first parameter depends on what a reasonable scale of spatial analysis in slum identification is. In a former study, which also provides further technical description of the algorithm and discusses ground truthing results (Kit et al. 2012), we showed that the slum morphology encountered in Hyderabad is best analysed in 60 m × 60 m units (the city features many small slum plots) scanned with a 6 m × 6 m overlapping sliding window (typical slum building size). These parameters were optimized in the cited study to generate a sharp threshold in lacunarity values reflecting the distinction between slum and non-slum morphologies for subareas where the spatial distribution of slum areas was identified during field data collection phase. The ground truthing process, described by Kit et al. (2012), consisted of visiting different parts of the city along predefined tracks, taking geotagged photographs and placing the photographs over the slum location map produced by the lacunarity-based algorithm.

Figure 7 shows this basic relation as calibrated for Hyderabad. Subareas with lacunarity values lower than 1.10 and larger than 1.90 exclude the existence of slum structures while the highest probability to find slum morphology (0.83) lies within the lacunarity interval of 1.10 to 1.15. For the subsequent intervals probability drops sharply and stays below 3% for all lacunarity values higher than 1.3.

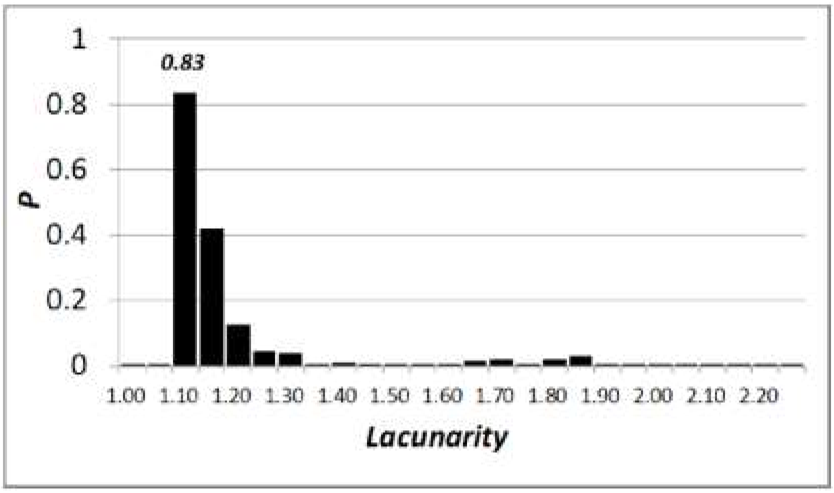


Figure 7. Algorithm validation. X-axis: lacunarity value of a 60 m × 60 m urban subarea of Hyderabad. Y-axis: probability that a subarea with a lacunarity value within the respective 0.05 interval represents slum morphology (after Kit et al. 2012).

Considering the probabilistic character of this remote sensing based approach, we find it reasonable to evaluate slum population in the city as expectation values for larger spatial units. The 146 wards of the Greater Hyderabad Municipal Corporation provide an appropriate level of spatial disaggregation, given that the official intra-urban slum population data is only available at the next coarser level of circles.

If *i* is the number of a subarea within a given ward, L_i is the lacunarity value for subarea *i*, P_i is the probability that subarea *i* shows a slum morphology and P^s is the population of a 1200 m^2 slum subarea in Hyderabad we obtain for the expectation value of the slum population within a ward, $P^S{}_W$,

$$E(P^S{}_W) = \sum_i p^S{}_i(L_i) \times P^S,$$

where the function $p^S{}_i(L_i)$ is depicted in Figure 7. This expectation value can be interpreted as “best guess” for a ward’s slum population as derived from remote sensing.

An inspection of the spatial distribution of the slum probabilities motivated a further step of analysis. We discovered that at the fringes of homogeneous slum areas these probabilities typically become smaller, either due to reduced densities or due to mixed (slum and non-slum) subareas. These areas mostly show lacunarity values greater than 1.15. Accordingly, we define a further expectation value, denoting a core slum population within a ward by evaluating the sum in the equation above only for summands with lacunarity values less than 1.15. This core, high density slum population is expected to correlate better to socio-economic indicators (e.g. population below poverty line) than the total slum population.

The described algorithm was applied to a 20 km × 20 km QuickBird scene from 2003 (covering the Municipal Corporation of Hyderabad and surrounding circles) which was converted into a binary picture by using a line detection algorithm (details provided by Kit et al. 2012).

In the next step we calculated the fraction of slum dwellers in each ward using census based ward-wise total population data. The election wards in Hyderabad are spatial units, designed to cover approximately equal numbers of people. The median total population of an election ward is 35,000 inhabitants, with ward populations ranging between 20,000 and 40,000 (GHMC 2009).

The authors are aware of the fact that the population density within a slum is a complex function of environmental and socio-economic factors that cannot be fully assessed using satellite image analysis only. Nevertheless, because we aim to estimate the number of people inhabiting slums of Hyderabad, we rely upon slum population density ranges calculated by compiling available sources of population and area data of individual slums as per Table 4.

Table 4. Calculation of slum population densities

Spatial unit name	Slum area, km²	Slum population, persons	Computed population density, persons/km²	Sources
Municipal Corporation of	22.33	1,195,204	53,525	MCH 2005; Centre of Good

Spatial unit name	Slum area, km²	Slum population, persons	Computed population density, persons/km²	Sources
Hyderabad Municipal Corporation of Hyderabad	22.33	1,411,000	63,189	Governance 2008 MCH 2005; Census of India 2001
Arsh Mahal slum	0.07	2,618	37,400	Centre of Good Governance 2008
Gulshan Nagar slum	0.05	2,173	43,460	Centre of Good Governance 2008
Indiranagar b Colony	0.02	1,605	80,250	Centre of Good Governance 2008
Rasolpoora slum	1.2	150,000	125,000	Chapligin 2006, visual slum boundary interpretation by authors

The paucity of available population data and limitations of a satellite imagery-based approach urged us to accept a broad range of slum population densities as equally probable, yielding a median value of 55,000 inhabitants per square kilometre, with lower and upper boundaries of 37,000 and 125,000 respectively. These numbers also cover Hyderabad's average slum density of 40,000 calculated by Adusumilli (2001) and is consistent with the numbers for similar urban agglomerations in India (Myllylä 2001; Baud 2009) reported in the literature.

In the last step, the remote sensing based results for all wards of Hyderabad were compared to existing statistics from the city administration on different aggregation levels. It is important to note that the fuzzy nature of official slum population figures in Hyderabad is indirectly confirmed by qualitative assessment of the results of several fieldwork periods in Hyderabad in 2009 and 2010, when the authors visited a number of slums in the city. Particularly, it has been observed that:

1. Not all neighbourhoods classified as slums by the local government give the impression of a high-density impoverished neighbourhood, and
2. not all neighbourhoods that appear extremely impoverished and informal are officially known to the local government, nor are they recognised as slums.

4. Results

The application of the method described above yields the following results:

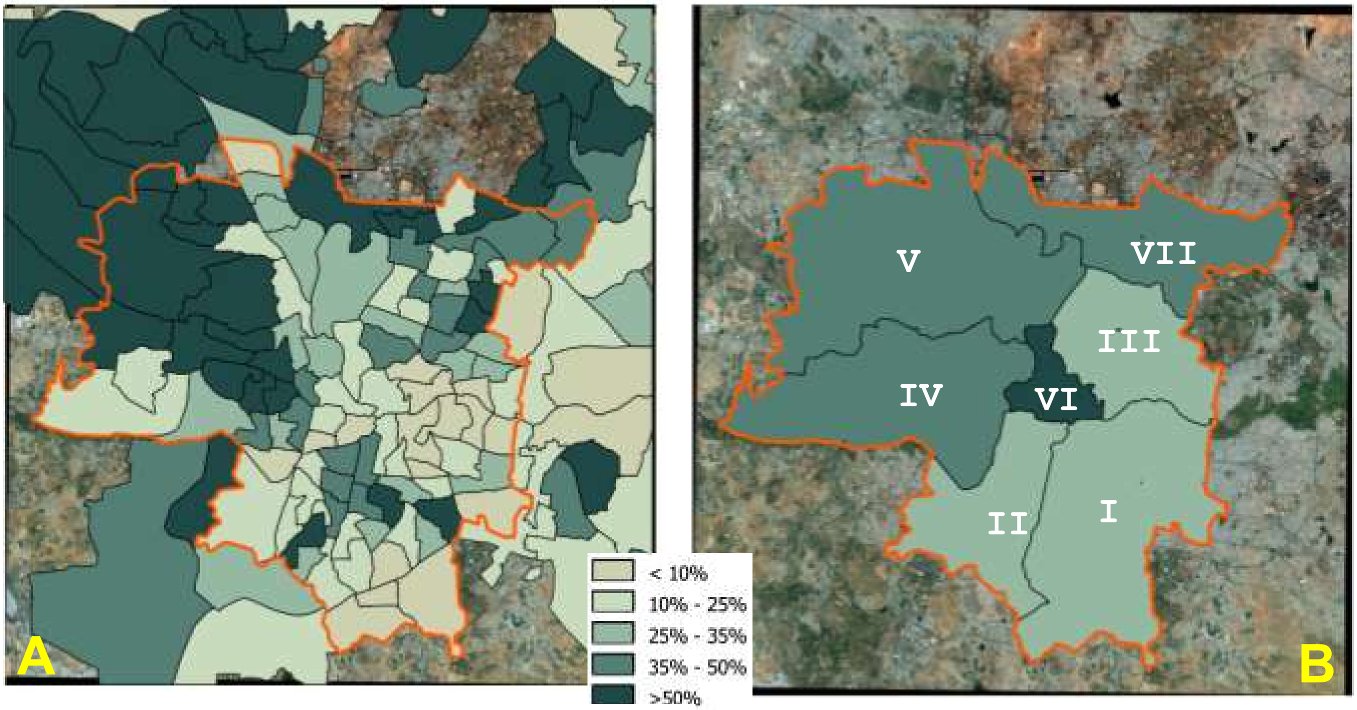


Figure 8. Algorithm verification. Image A: Estimated percentage of slum population relative to total ward population. Image B: Percentage of slum population relative to total administrative circle population.

Figure 8 compares the remote sensing-based slum population share within election wards in Hyderabad (A) to the best available slum population statistics which are limited to the data collected by the Municipal Corporation of Hyderabad at the urban circle level (B). Both datasets indicate a higher proportion of slum population in the north-eastern part of the city. At the same time, the methodology presented by this paper allows for a finer spatial resolution of the urban slum distribution.

The calculated expectation value of the slum population share for the whole of Municipal Corporation of Hyderabad is 29%, which is less than the 35% provided by Census 2001. The calculation also suggests that only 13% of Hyderabad is a core slum, with the remaining 16% assigned to intermediate slum class.

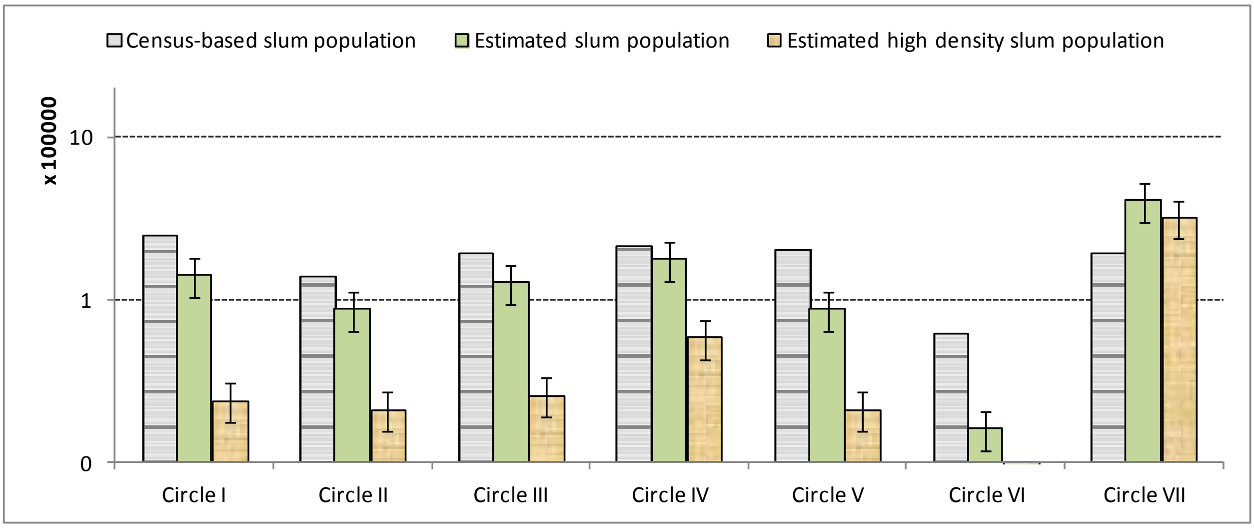


Figure 9. Circle-wise comparison of multiple-source slum population figures.

Figure 9 combines circle-wise slum population figures provided by the Census of India, 2001 with those statistically estimated using slum detection algorithm, with error bars indicating probability ranges derived from upper and lower boundaries of slum population density. The median remote sensing-based population figures of all circles apart from circle VII are estimated to host lower slum populations than provided by census. Only circle VII is estimated to be populated by more slum dwellers than the official figures suggest, with conservative core slum population estimates exceeding census data by 10%. Circle VII is indicated to host the highest number of slum population, and circle VI – the lowest. Core slums account for the majority of slum population in circles IV and VII, but are virtually non-existent in the circle VI.

5. Discussion

Satellite imagery is a snapshot in time that covers the complete area of the city. It is not dependent on historical slum notification and recognition processes meaning that a slum identification technique which is based on remote sensing data is well positioned to address the issues of changes in urban morphology caused by slum upgrading processes as well as rapid establishment of new slums. Many of the areas considered to be slums by local authorities and subsequently reported as such by the census might have lost their slum nature (but not the slum status) over the years between their establishment and census data collection – an assumption which is supported by the results of a slum-based child labour survey in Hyderabad in 2007 (Centre for Good Governance 2008).

The ward level slum population map (Figure 8-A) is generally consistent with the coarse resolution official statistics and unofficial reports, reporting high percentage of slum population in the north and north-west of the city. The majority of the population of 21 out of 144 wards within the MCH boundaries is estimated to consist of slum dwellers. The higher concentration of slums in the north-west of Hyderabad is best explained when viewed in conjunction with industrial development pattern within the city. Many of the industries in the northern rim of the city use low-skilled, low-paid labour provided by slum dwellers, and establishing a slum in the vicinity of work (a large construction site, a quarry etc.) reduces the need to travel and creates financial and time benefits for workers.

The comparison of slum population percentage maps (Figure 8) and circle-wise slum population numbers (Figure 9) indicate that while the method provided by this paper succeeds in capturing spatial pattern of slum locations in Hyderabad and does so at a much finer scale than previously available data. The remote sensing-based slum population figures tend to deviate from the official ones for the most of the city. Particularly, the slum detection algorithm estimated considerably lower presence of slums in the inner city of Hyderabad (circle VI) than reported by official statistics.

While several site visits to Hyderabad by authors did reveal a traditionally dense housing pattern and a considerable degree of poverty in circle VI, the results of the fieldwork allow us to consider the official slum population figure for this circle of 52% to be an unlikely high value[1]. The census-based statistics indicates that approximately 14% of the population in Hyderabad lived below the national poverty line in 2001 (MCH 2005). Because the aggregate remote-sensing based slum population ratio in the city is 36%, it is highly likely that this city belongs to the places reported by Satterthwaite (2004), where systemic under-estimation of the percentage of households falling below the poverty line takes place. This is also supported by a study by Agarwal (2011), who found that 76% of Hyderabad's poorest population does not live in census slums.

This paper by no means seeks to establish the direct link between poverty levels (particularly calculated in such a complex way as in India, where the type of house is only one of 13 parameters used to assign poverty rating to a household) and slums; the possibility of a genuine correlation in the urban context of India is, however, worth exploring. After all, the slums including unlisted poverty clusters have the highest concentration of poor people and often the worst living conditions (Agarwal 2011).

The authors are aware that the absolute slum population results presented in this paper are sensitive to slum population density figures, which obviously vary among different cities and slums within the same city and depend on a wide range of factors immeasurable by remote sensing methods. The same holds true for the reliability of the method as such – most of the properties of a slum (land tenure

[1] The circle VI covers the historic centre of Hyderabad, which has been assigned ('notified') slum status by the authorities of the city at the early stage of slum notification process. Several expert interviews stressed very limited willingness of slum inhabitants to de-notify the slum they live in even if it does not qualify for slum status, because of preferential tax treatment or access to subsidised goods and services. We did not collect enough hard evidence to support this claim because this was not the main purpose of this paper, but we are working on another publication which looks into the spatio-temporal details of official slum reporting in Hyderabad and discrepancies between the numbers reported and situation on the ground.

situation, availability of services such as drinking water and sanitation etc.) cannot be established from a satellite, and housing density is certainly not a completely reliable proxy for slum identification. Nevertheless, the satellite imagery-based slum population assessment can provide meaningful insights into slum distribution patterns at spatial resolutions and time scales unavailable to local administrations in the urban context of India.

6. Summary and conclusions

This study confirms suitability of lacunarity-based slum identification for slum studies in Hyderabad. The method not only provides the tools to identify individual slums and their clusters, but also provides meaningful aggregate statistics which are comparable to data collected during censuses.

Apart from providing slum population estimated for the whole Hyderabad, this approach allows for identification of wards with the highest slum population. This data is particularly important for local decision-makers because no official and reliable ward-wise slum population data is collected in Hyderabad. The present study supports the recommendation of Agarwal (2011) to India's city authorities to frequently update official slum lists maintained by them; the approach outlined in this paper can facilitate this process.

However advanced, remote sensing alone cannot be used to assess such complex issue as slums and slum population. Used in conjunction with other methods, however, it may prove to be an important component of an urban stakeholder's toolbox, e.g. in the process of designing criteria for slum resettlement. The advantage of the remote sensing based method lies in the comprehensive spatial and temporal coverage in high resolution. The disadvantage is the restriction to physical urban morphology. Depending on the scientific objectives, the results may only hint at locations of specific physical change which then have to be investigated more closely by other means or may already give a large part of the answer, e.g. for the investigation of sensitivity towards climate change.

Another way to use the remote sensing methods in slum population assessment is to reconstruct spatial and temporal slum development during the last two decades, as restricted by availability of appropriate high resolution satellite images. This would allow testing various slum development hypotheses and can constitute a promising contribution to the analysis of possible future dynamics of urban agglomerations of the South.

7. Acknowledgements

The authors acknowledge financial support from the Federal Ministry of Education and Research of Germany (BMBF) under the project "Future Megacities".

Chapter IV:
Automated detection of slum area change in Hyderabad, India using multitemporal satellite imagery

ISPRS Journal of Photogrammetry and Remote Sensing 83: 130-137

Oleksandr Kit and Matthias Lüdeke

© 2013 Elsevier Ltd. All rights reserved.

doi: 10.1016/j.isprsjprs.2013.06.009

Received 28 February 2013; revised 5 May 2013;

accepted 27 June 2013.

Abstract

This paper presents an approach to automated identification of slum area change patterns in Hyderabad, India, using multi-year and multi-sensor very high resolution satellite imagery. It relies upon a lacunarity-based slum detection algorithm, combined with Canny- and LSD-based imagery pre-processing routines. This method outputs plausible and spatially explicit slum locations for the whole urban agglomeration of Hyderabad in years 2003 and 2010. The results indicate a considerable growth of area occupied by slums between these years and allow identification of trends in slum development in this urban agglomeration.

1. Introduction

Despite all the multi-scale efforts, slums continue to shape considerable part of many large urban agglomerations in developing and newly industrialized countries as of 2013. It is generally accepted that highly crowded, underserviced and dilapidated informal settlements (UN 2011a) are currently home to approximately 828 million people (UN 2012). Rapid urbanisation, social and demographical change and weakness of institutions have all contributed to the fact that the slum population of India remains being the highest in the world (UN 2012). According to official figures, 22% of the total population of India’s cities and, more specifically, 35% of the population of the city of Hyderabad lives in slums (Census of India 2001). The Government of India (Government of India 2010c) expects country’s slum population to exceed 100 million by 2015.

The reliability of national sample surveys and other official statistics on slums in India has often been questioned in the literature (Satterthwaite 2010; Agarwal, 2011; Risbud 2010), while the cause of errors has been often attributed to the stealthy nature of slums and difficulties of data collection. Hyderabad is not an exception: a survey carried out by the Centre for Good Governance in 2008 stumbled upon a problem that 146 slums from the slum list that the Centre obtained from the Municipal Corporation of Hyderabad did not exist at the time of the survey. Furthermore, 21 slums were replaced by multi-level apartments, shopping centres etc (Centre for Good Governance 2008).

Discussing different methods of data acquisition for mapping of slums, Kohli et al. (2012) distinguishes between census-based, participatory and remote sensing-based approaches. Counting individual dwelling units in situ is undoubtedly the most reliable method of slum area estimation. Although very accurate, this method is extremely time- and effort-intensive. Satellite imagery of cities only reflects the spatial and spectral morphology of urban fabric and cannot replace traditional socio-economic data collection methods. Nevertheless, it has been proven that spatial characteristics of land cover elements such as rooftops, soil, and vegetation can serve as proxies for the identification of both slum-like areas and residential areas associated with higher socioeconomic status (Weeks et al. 2007). Remote sensing and advanced image processing methods have the potential to offer a worthy alternative to field data collection in certain situations. By virtue of its uniformity, satellite imagery is a useful tool to address the paucity of data on urban settlements in the global South and belongs to an active field of research on urbanisation patterns in developing and newly industrialised countries.

Successful examples of slum identification from very high resolution imagery include methods based on object-based image analysis (Hofmann et al. 2008), object segmentation and classification (Shekhar 2012), morphological opening and closing (Rhinane et al. 2011). One of the last successful attempts to automatically identify slums in India has been made by Shekhar (2012), where eCognition-supported object segmentation and classification has been used to identify slums in Pune. The author reaches identification accuracy of 87% as benchmarked against the slum survey using classification rules such as structure size and density, street pattern irregularity and vegetation distribution. Characteristic physical features and heterogeneity of urban morphology have been used by Taubenböck and Kraff (2013) to delineate a set of slum areas in Mumbai from a morphological point of view and to confirm their separability from formal settlements.

The slums in a city do not evolve overnight. Establishing and disappearance of slums is a steady process that which may take anything from days (in case of slum removal actions) to decades. Many of the studies mentioned above have been successful in employing automated or semi-automated methods to identify slum extent from a single satellite scene, but surprisingly few studies so far addressed the multitemporal dimension of slum identification in the same city. This is on one hand explained by limited temporal availability of very high resolution satellite imagery obtainable at reasonable costs, and on the other hand – by imperfectness of automated slum identification methods.

Nevertheless, this field of research is not completely barren. QuickBird and GeoEye imagery has been successfully used by Veljanovski et al. (2012) to analyse settlement growth and changes in Kibera slum, Nairobi using object-based contextual classification methods between years 2006 and 2009. Jain (2007) analysed slum evolution between 2001 and 2005 in Dehra Dun, India using manual visual interpretation techniques of Ikonos imagery. These studies were, however, either confined to parts of urban agglomerations or analysed relatively small cities.

This work continues and enhances previous studies in the field by Kit et al. (2012) and Kit et al. (2013). It is not limited to improvement of automated slum identification methods developed earlier, but goes a step further and attempts to capture the spatio-temporal dynamics of urban fabric change in Hyderabad by analysing slum-related land use change in the whole megacity area between the years 2003 and 2010.

2. Study area

Hyderabad is the capital of Andhra Pradesh state in central South India. It grew from about one million inhabitants in 1951 to about seven million in 2001. The urban agglomeration is expected to host 10-million inhabitants by around 2020, whereas the scenarios for the wider urban area project population size of 13 million in 2021 and 18 million in 2031 (HMDA 2011).

According to the GHMC commissioner as quoted by The Times of India (2012), Greater Hyderabad hosts 1476 slums, 1179 of which are notified. 66% of the city's total slum population of 1.7 million live in the core area (erstwhile MCH), while the rest lives on the periphery of the city. The official datasets available through different local government agencies (Figure 10) are very fragmented and are neither consistent between each other, nor plausible when compared to the satellite imagery. While the total number of slums within the MCH as reported by the Hyderabad Urban Development Authority in 2003 (HUDA 2003) is roughly similar to the one reported by the Greater Hyderabad Municipal Corporation in 2005 (GHMC 2005): 811 vs. 1142, their spatial distribution is different, with only 25% of slums matching each other's location within 100 m buffer. Furthermore, no data is provided for the urban area outside of the MCH core.

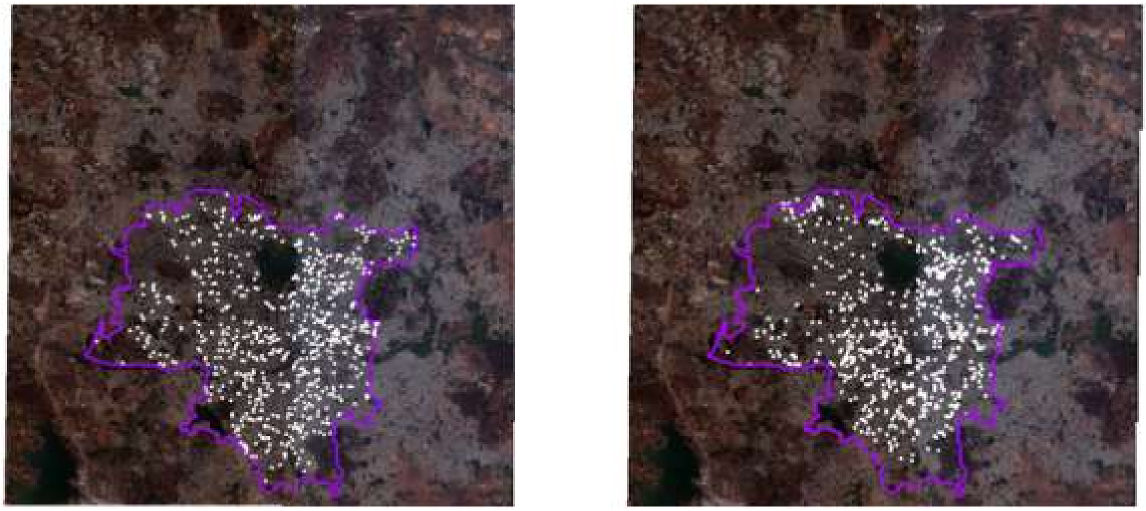


Figure 10. Official slum maps of Hyderabad according to HUDA, 2003 (left) and GHMC, 2005 (right).

The automated slum detection algorithm has been applied to the following imagery:

- QuickBird full swath (11 bit) cloudless mosaic, acquired on 27 May and 11 June 2003, and
- WorldView 2 full swath (11 bit) cloudless mosaic, acquired on 3 and 14 February 2010.

The imagery used in this study was delivered by the data provider as a gridded dataset which was radiometrically calibrated, pan-sharpened, corrected for sensor-and platform-induced distortions and mapped to a UTM projection zone 44N. The data covers 400 km^2 of urban territory within a rectangular bounding box of 78° 22”-34” east longitude and 17° 18”-30” north latitude; this corresponds to the image size of 38,144 by 68,287 pixels.

3. Methodology

The starting point of our analysis is the relation between the lacunarity value of a 60 × 60 m (100 × 100 pixels) image of an urban subarea and the probability that this subarea is morphologically similar to a slum. Lacunarity is a specific measure of spatial heterogeneity that identifies the granularity of the visible urban structure. It is sensitive to quasi-regularly repeated small objects and an elaboration of structural measures like the fractal dimension (Amorim et al. 2009). Lacunarity has been successfully used for slum identification in Hyderabad by Kit et al. (2012).

A very sensitive part of the lacunarity-based slum detection algorithm is the preparation of binary images describing the surface. In an ideal case, all housing units within a city would be marked as 1, and everything between them – as 0. This is, however, barely possible to achieve when performing automated satellite imagery analysis in a city like Hyderabad, where vectorised housing maps are not readily available and the housing structure in many neighbourhoods is highly informal. Where human eye can quickly comprehend a scene and identify artificial features such as individual buildings irrespective from dwelling unit size or roof material variability, a computer algorithm requires multiple preparatory steps. Therefore, it was important to design a binary data preparation routine which would be successful in converting true-colour satellite imagery of a city into binary raster of pseudo built-up areas (Owen and Wong 2013).

Automated multitemporal urban satellite imagery analysis is sensitive to the position of the sun because of the difference in shadows across multiple images. Shadows are a particular problem for high resolution imagery, where a shadow from a typical one- to three-storey house in India can stretch across several pixels of the image and therefore considerably reduce the object identification and object comparison quality. Typical cloud-free urban satellite imagery is very often assembled from a mosaic of scenes, recorded during satellite revisit flights. Therefore, the position of the sun varies not only between multi-year imagery sets, but also within a one-year scene. Even though imagery providers typically include the exact time of imagery acquisition (and hence the height of the sun over horizon) for every piece of the mosaic, correction of shadow effects in high resolution images of urban areas is a very complex and error-prone task (Zhan et al. 2005). Therefore, we were looking for an urban fabric analysis algorithm which would be rather insensitive to the shadows and would mainly identify the edges of buildings.

Veljanovski et al. (2012) cites the discrepancy between informal area outer-homogeneity and inner-heterogeneity due to the microstructure of urban agglomeration as one of the reasons why automated object delineation (and thus object-based analysis) in slum-like areas often produces poor results. Generation of binary maps which carry object/non-object signals and are suitable for temporal analysis therefore remains a problematic step of automated urban slum identification methods. Our earlier studies used principal component analysis (PCA) and Gaussian line detection algorithms to correctly identify slums on a 2003 image, but were less successful to produce consistent and ground truth-verified results with multitemporal satellite imagery obtained from two different platforms. To overcome this limitation and to perform a fully automated detection of slum area change in Hyderabad, after a thorough comparison of several methods of binary raster generation we decided to use a combination of two advanced image analysis methods: canny edge detection and LSD straight line detection. We tested the Laplacian of Gaussian edge detector as well, but ruled it out after the analysis of data provided by Figure 11 and Table 5.

Laplace of Gaussian

The Laplacian of the Gaussian is an edge-detection filter which highlights regions of rapid intensity change on an image that has been Gaussian-smoothed to reduce its sensitivity to noise. It is commonly used as a second-order edge detector in image processing (Gunn 1999). The method was proposed by Marr and Hildreth (1980), as a physiological model of the early human visual system. The filter has been successfully used to analyse satellite imagery of urban areas and perform feature extraction by Bong et al. (2009) and Ünsalan (2009).

Canny

Canny detector is a powerful edge detector that generates single-pixel wide continuous lines along the significant edges within an image (Canny 1986). It is widely regarded as the edge detection standard. This is a multistage algorithm which combines Gaussian noise reduction, non-maximum suppression and hysteresis thresholding of an image. It is adaptable to various environments and has been repeatedly used in object extraction and land use studies using high resolution urban satellite imagery (most recent applications include Peeters and Etzion 2012; Awrangjeb et al. 2010; Grigillo et al. 2012).

LSD line detection

LSD straight line detection algorithm is an automated image analysis tool which is aimed at identifying locally straight contours on images (von Gioi et al. 2012). It takes a grey-level image as input and returns a list of detected straight line segments. Its application to urban and periurban remote sensing included separation of formal and informal settlements in Algeria (Khelifa and Mimoun 2012), extraction of buildings (Poulain et al. 2011) or landscape analysis (Bailly and Levevasseur 2012). Combined with LIDAR data, line segment detection as implemented by Awrangjeb et al. (2012) has been successfully used to detect buildings in complex urban setting.

Figure 11 presents a sample of the original satellite imagery and the binary datasets obtained using each of the data preparation methods described above.

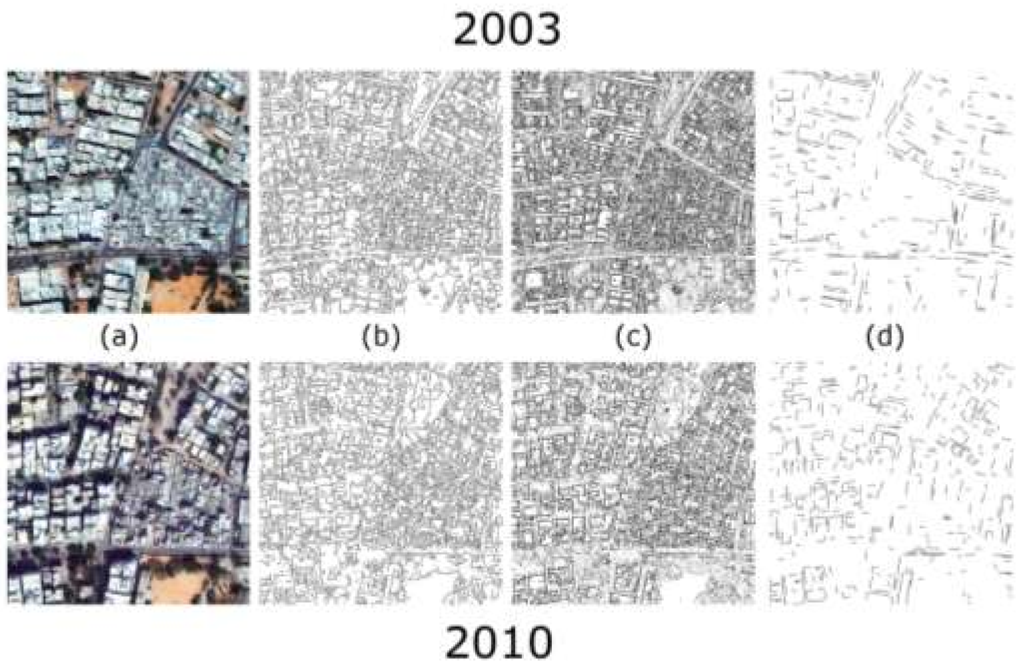


Figure 11. Comparison of original satellite imagery (a), Laplacian of Gaussian (b), Canny (c) and LSD (d) binarisation algorithms for 2003 and 2010 scenes.

The comparison of performance and comparability of binary image generation methods used an extract of the satellite image (Figure 11, Parvath Nagar area in the north-western part of the city) where the observed land use change between 2003 and 2010 has been utterly insignificant. The goal of this step was to identify a method which would produce the most similar binary maps for both time slices in question. To quantify similarity of images, we computed and compared lacunarity values for all binarisation methods and time slices. The results are presented by Table 5:

Table 5. Lacunarity values for binary images representing area which did not change between 2003 and 2010.

	Laplace of Gaussian	**Canny**	**LSD**
2003	1.07	1.13	2.52
2010	1.11	1.15	2.03
Difference:	0.04	0.02	0.49

This analysis allows us to conclude that Canny edge detection method produces the smallest difference in the lacunarity values between two time slices, meaning that the algorithm ensures the highest degree of morphological similarity between both binary images. Visual analysis of the images confirms this conclusion.

The final pre-processing algorithm combines the strengths of Canny edge detection and LSD line detection methods. Canny edge detection is capable to correctly outline sharp edges within a satellite scene. In many cases these are roof-street or roof-roof boundaries. However, the algorithm identified many other sharp boundaries within the city, such as these within park and agricultural zones, road elements, or, especially, exposed rock formations. In many cases the spectral signatures of such morphological areas are very similar to housing regions, making it very difficult to exclude them from the slum identification process. The distinctive signal which reasonably well distinguishes human habitations from exposed rocks is the rectangular shape of individual features within the area, as human settlements in India and especially these in slums tend to consist of straight-lined structures.

This was the reason behind decision to perform one more data processing step and to exclude areas which contained less than 2 LSD points per 100 × 100 pixels square. The 2 pixel threshold has been obtained empirically as such that reasonably well excludes rock formations and vegetation forms in Hyderabad without influencing human settlements.

Figure 12 summarises automated slum identification process in a flowchart.

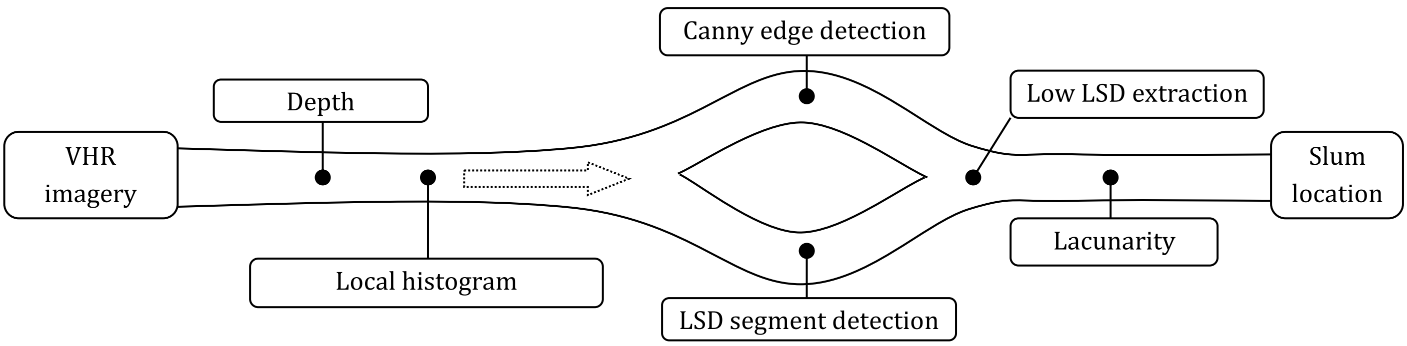
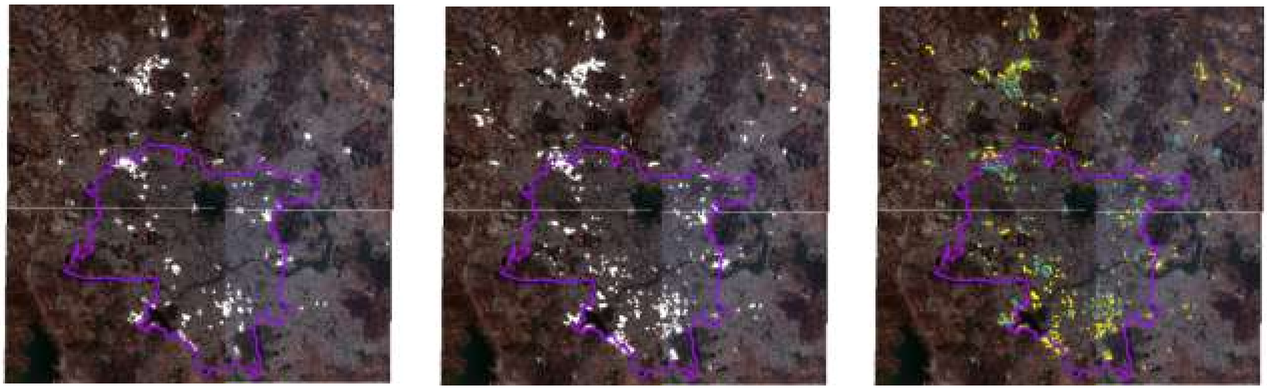


Figure 12. Slum identification algorithm flowchart.

The authors used VIPS image processing system[2] in conjunction with scikit-image[3] and LSD[4] libraries and a custom developed lacunarity calculation routine in a mixed C++/Python programming environment. This final algorithm performed equally well on 2003 and on 2010 imagery and did not require additional calibration or modification, neither between different components of the satellite mosaic nor between the time slices.

4. Results

The application of the slum identification method described above yields the results depicted by Figure 13, which compares identified slum locations in Hyderabad in 2003 to these in 2010.



a) Detected slums

b) Detected slums

c) Difference map (yellow: new slums, blue – disappeared slums

Figure 13. Automatically identified slums of Hyderabad in 2003 and 2010.

The full resolution KML files containing data shown in Figure 13 are provided as the multimedia attachment to this article. The spatial distribution of slums in both scenes is relatively similar and is confined to the outer circle of the city and to the Old Town on the right bank of river Musi. The most substantial difference between these two time slices is an overall increase in existing slum area, as well as establishment of new slums in the south and in the north of the city. The results of automated slum identification indicate a 70%- increase of the area covered by slums between 2003 and 2010, approximately from 11 to 19 km^2. Very few

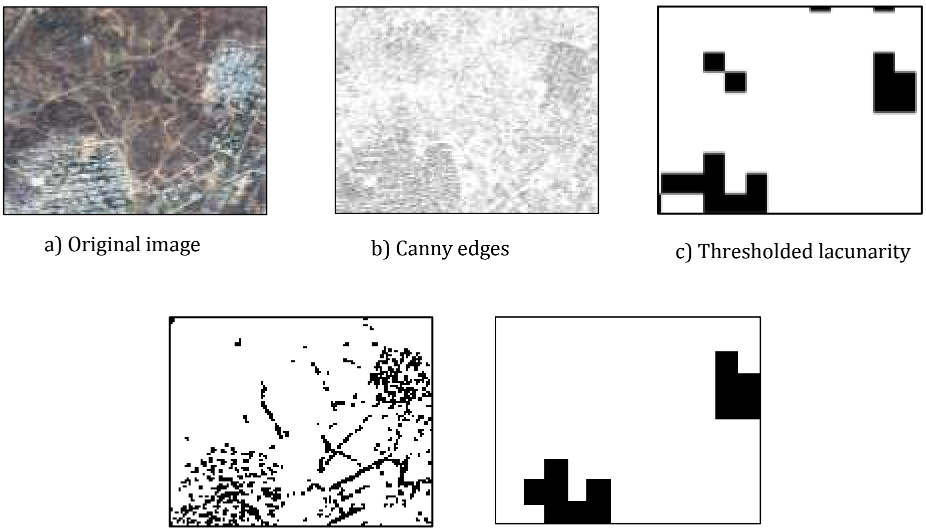
[2] http://www.vips.ecs.soton.ac.uk

[3] http://scikit-image.org

[4] https://github.com/theWorldCreator/LSD

informal settlements appeared on previously completely uninhabited land, the vast majority of slum areas evolved in the process of densification of more spacious settlements or as the result of growth of existing slums, conforming to a typical slum growth process described by Sliuzas et al. (2008).

The importance of combination of Canny and LSD algorithms for error reduction in slum identification process is demonstrated by Figure 14. It depicts a very heterogeneous area which combines rock formations, vegetation, slum and non-slum land use types in the vicinity of the Muzaffar Ahmad Nagar slum in the Miyapur part of the city (Figure 14-a). The lower and the right part of the image are occupied by slums; the upper part – by exposed rock formations. Because of high contrast to the surrounding terrain and high density of distinct features, these areas produce similarly dense Canny line patterns (Figure 14-b) and therefore yield similar lacunarity values (Figure 14-c). The only difference of a built-up area is the density of straight lines, and these are captured by the LSD algorithm only (Figure 14-d). The final lacunarity raster only contains cells on the bottom and on the right of the subset, and these are slum cells (Figure 14-e).



a) Original image b) Canny edges c) Thresholded lacunarity

d) LSD segments e) Final thresholded lacunarity

Figure 14. Example of combination of Canny and LSD algorithms for slum identification.

The ability of the algorithm to analyse different time scenes and to document slum establishment process using multitemporal imagery from different sensors is demonstrated by Figure 15, which reveals changes in slum coverage in the I.S.Sadan area of Hyderabad. The previously large open space area in the centre of the image (Figure 15-a) has been built up by two types of housing: modern high-rise residential blocks and a Π-shaped high density slum (Figure 15-b), which probably hosts construction labourers and servants. The shape and extent of the newly established slum have been correctly identified by the algorithm (Figure 15-c).

a) 2003 b) 2010 c) Slum identification

Figure 15. Establishment of a slum at I.S.Sadan area.

To verify the performance of the algorithm and the quality of slum identification, a series of ground truthing visits has been conducted (Bostel, 2012). In total, 8 evenly distributed ground truth sites with positive identification signals produced by the algorithm have been selected (Figure 16, points 1-10), 7 of which (87%) confirmed presence of slums in that area. The results of ground truthing are summarised in the Table 2, the on-site area description followed the Indian building typology by Baud et al. (2010).

The 2003 slum map has been compared to the slum map of Hyderabad obtained through an earlier lacunarity-based slum detection algorithm published by Kit et al. (2012). All the ground truth sites used in the earlier study were matched by the new algorithm (Figure 16, points A-C). While both approaches identified the same slum clusters within the central part of the city, the new method yielded considerably higher concentration of slums in the south of the city. This constitutes an improvement in accuracy of slum identification – a finding which is confirmed by visual analysis of the satellite imagery and by ground truth visits.

Additionally, the results of detailed slum surveys reported in the literature (Addagutta slum as reported by Shashi Mohan and Vijaya Lakshmi, 2012; Road Number 5/7 slum as reported by Times of India, 2013) were plotted on the map (Figure 16, points x-y). Both slums are reported to occupy approximately the same area since 1970s, and the automated algorithm was capable to capture both their existence and the absence of significant change in the slum area between 2003 and 2010.

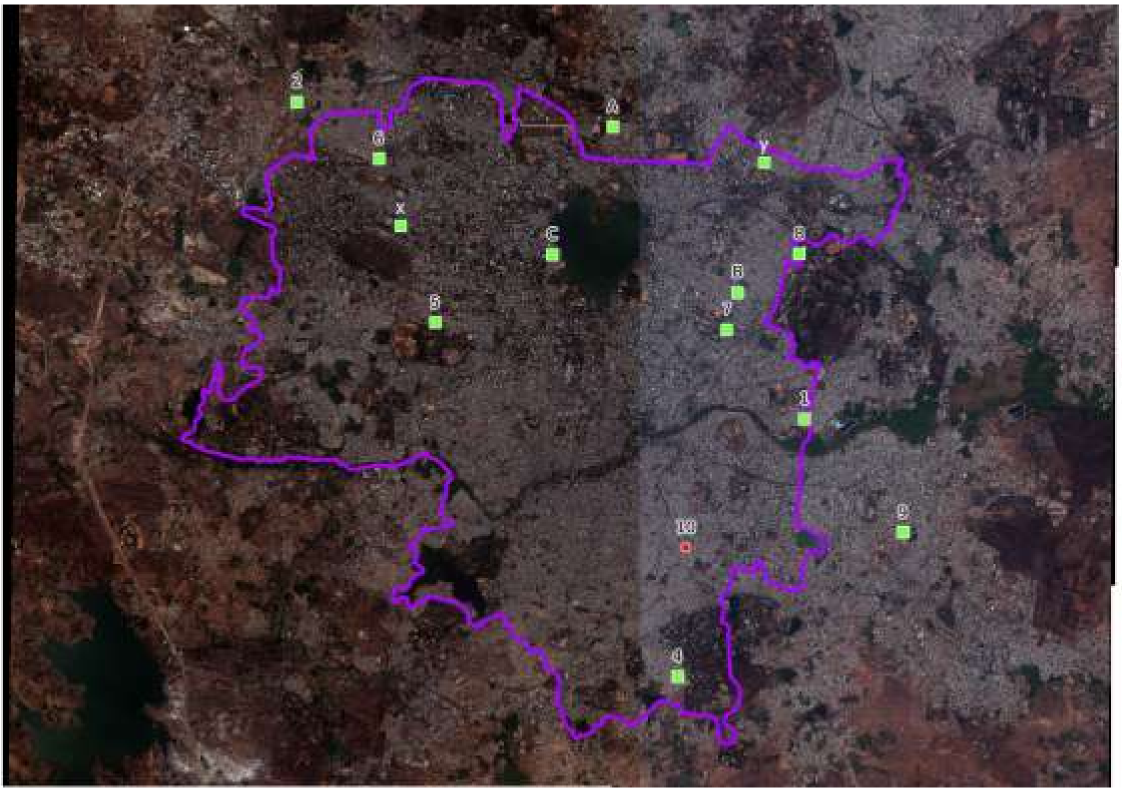


Figure 16. Ground truthing sites (green – positively identified slums, red – false identification; 1-10: sites by Bostel 2012, A-C: sites by Kit et al. 2012).

Table 6. Ground truthing

Point	Satellite image description	Algorithm result	On-site area description	Ground truthing result
Point1	Large, homogeneous and very dense settlement	Slum	Informal and basic built-up, very narrow streets	Slum
Point 2	Small and very dense settlement	Slum	Basic built up, very narrow streets	Slum
Point 4	Large, homogeneous and very dense settlement	Slum	Basic built up, very narrow streets	Slum
Point 5	Stretch of very dense settlement within a low-density settlement neighbourhood	Slum	Informal and basic built-up, very narrow streets	Slum
Point 6	Large, homogeneous and very dense settlement	Slum	Informal built-up	Slum
Point 8	Medium-sized very dense settlement	Slum	Basic built-up	Slum
Point 9	Medium-sized very dense settlement	Slum	Informal and basic built-up, very narrow streets	Slum
Point 10	Large and dense heterogeneous area in the inner city	Slum	Traditional built-up, not so narrow streets	Not slum

5. Discussion

The results laid out in section 4 indicate that the sub-metre satellite imagery is a suitable data source for identification of slums in Hyderabad using advanced image analysis techniques. Satellite imagery is a snapshot in time that covers the complete area of a city. It is not dependent on historical slum notification and recognition processes, meaning that a slum identification technique which is based on remote sensing data is well positioned to address the issues of changes in urban morphology caused by slum upgrading processes as well as rapid establishment of new slums.

Spatial distribution of new slums in Hyderabad clearly identifies two major zones of slum growth: the north and the south of the city. Both regions are the areas of industrial growth in the city, offering extensive low-skilled job opportunities in construction and production sectors. Establishing a slum in the vicinity of work (a large construction site, a quarry etc.) reduces the need to travel and creates financial and time benefits for workers.

The surprisingly high density of slums within and on the edges of upper class housing estates of Banjara and Jubilee Hills is the consequence of high demand for low-skilled and low-paid domestic services by the wealthy inhabitants of these parts of the city (Sengupta 2009). The Old Town on the right bank of the Musi river, which is also characterised by high slum occurrence, is locally known to host a large fraction of poor and predominantly Muslim population inhabiting low-quality housing units.

Setting the approximate slum population density at 55,000 inhabitants per square kilometre and lower and upper boundaries at 37,000 and 125,000 respectively (for literature review and reasoning of the numbers see Kit et al. (2013)), we perform a very rough first order quantification of slum population numbers in Hyderabad in 2010, which ranges between 700,000 and 2.3 million, with 1 million being the most probable value. Compared with 2003 numbers this means an impressive increase from approximately 600,000 slum inhabitants in 2010 (upper and lower probability boundaries 400,000 and 1.4 million).

Although every effort to establish high level of slum identification accuracy has been made, the authors are aware that the proposed algorithm is not fail-proof and may produce erroneous and sometimes misleading results, especially when applied outside of the urban context of India. Specifically, the authors anticipate the source of error to be principally attributed to shape and size of slum-constituting elements. The combination of Canny and LSD image pre-processing steps may not be sufficient to identify slums which do not consist of rectangularly shaped dwelling units (such as makeshift irregular-shaped houses in some parts of Africa or Asia). The intra-slum morphology of a slum that can be detected using the lacunarity-based algorithm is also depended on the existence of a clearly defined boundary between houses, which excludes slums that consist of multiple dwelling units sharing the same roof.

The automated slum identification algorithm is also limited in the size of slums it is capable to identify. Kit et al. (2012) tested multiple lacunarity matrix and floating window sizes before concluding that floating window of 10 × 10 pixels applied to lacunarity matrix of 100 × 100 pixels is optimal for slum identification purposes. This, however, effectively limits the algorithm to detecting slums that are equal or larger than 100 × 100 pixel subsets, which translates into 3600 m^2 at the satellite imagery resolution used for this study. Authors' experience of experimenting with smaller matrix sizes suggests that the increase of error rate effectively counteracts any improvements in identification of smaller slums.

6. Summary and conclusions

Combination of Canny edge detection, LSD segment detection and lacunarity provides a powerful and robust instrument for rapid automatic identification of informal settlements in the urban context of India. It offers a way to rapidly perform edge delineation, exclude non-linear features and ultimately calculate lacunarity as a proxy of slum probability in every of the approximately 260,000 of 3600 m^2 cells on a 2.6×10^9-pixel satellite image covering urban area of Hyderabad. The new method has produced two coherent and unbiased snapshots of Hyderabad's slum coverage in 2003 and 2010 and constituted the first ever successful attempt to automatically process multitemporal very high resolution satellite imagery of a whole city.

This study proves the usefulness of advanced image processing methods in urban land use change detection research in a slum-plagued megacity of Hyderabad. It provides an insight into spatio-temporal slum development patterns in the city and questions the data collection procedures and the performance of counter-slum measures of the local administration between 2003 and 2010. It identified three trends in slum growth in Hyderabad, namely densification of existing settlements, slum growth on the fringes ('slum overflow') and spatial focus of slum growth in the north and in the south of the city.

It is worth mentioning that, as an aggregate function, lacunarity is obviously not capable to identify slums which are smaller than the resolution of the lacunarity matrix (100 × 100 pixels, 3600 m^2). Therefore, the methodology described in this paper should be only used to identify slums occupying more than 3600 m^2.

The methodology suggested by this paper can be used to assess the performance of urban management practices in different parts of Hyderabad and probably – in other large urban agglomeration across the Indian subcontinent. The Government of India and the administration of Hyderabad frequently report about the progress towards reaching the slum-free cities goal. The use of rapid remote sensing-based slum assessment techniques is a meaningful way to perform the first-order slum assessment process and to identify areas that require further attention. Better availability of data will facilitate development of appropriate policies and efficient measurement of progress towards reaching Target 11 of the Millennium Development Goal 7: 'By 2020, to have achieved a significant improvement in the lives of at least 100 million slum dwellers'.

One of the key advantages of the algorithm is its complete reliance on free open source software tools and very modest hardware requirements. Reasonably low costs of the method result in an increased ability to analyse more data, making this approach suitable in financially tight situation of many cities of the global South. In situations where funding constraints make impossible the acquisition of multi-temporal very high resolution imagery, an alternative ASTER-based approach suggested by Stoler et al. (2012) may be used as well.

If combined with extreme precipitation-induced flood risk map of the city (Kit et al., 2011), this study can identify newly established slums which settle on the most endangered sites. Since many of them consist of temporary housing units and lack the solidity of the infrastructure of long established slums, such settlements can be classified as particularly vulnerable ones. The authors believe that the results of slum detection using the algorithm proposed in this paper can be used to prepare a subset of the areas of interest to be analysed using other, less automated methods such as the generic slum ontology proposed by Kohli et al. (2012).

The authors are highly interested to apply the methodology on other cities in the developing world and invite the international research community to cooperation. The next steps of this research will consist of acquisition and analysis of very high resolution satellite imagery from other cities of India, and in further improvement of algorithm accuracy. The enhancement of the pre-processing algorithm shall lead to better identification of house boundaries, accompanied by better suppressing of false signals. This may be achieved through employment of spectral classification algorithms for exclusion of non-urban areas, implementation of a sun height-based shadow removal algorithm or other satellite imagery-based building recognition methods.

7. Acknowledgements

The authors acknowledge financial support from the Federal Ministry of Education and Research of Germany (BMBF) under the project “Future Megacities”.

Chapter V:

Assessment of climate change-induced vulnerability to floods in Hyderabad/India using remote sensing data

Book chapter: Konrad Otto-Zimmermann (Ed.) *Resilient Cities* 1 (2): 35-44.

Oleksandr Kit, Matthias Lüdeke and Diana Reckien

© 2011 Springer Science+Business Media B.V.

doi: 10.1007/978-94-007-0785-6_4

Received 20 May 2010.

Abstract

The frequency and intensity of extreme rainfall events over Hyderabad, India, are often the cause of devastating floods in the urban and periurban areas. This paper introduces a quantitative approach to assessing urban vulnerability to floods in Hyderabad, both identifying informal settlements via high resolution satellite photography and through the development of a flood model for urban and periurban areas.

Introduction

The projections of future climate patterns in South Asia suggest the increase in frequency and scale of extreme precipitation events and particularly amplify the risk of significant urban floods. This is especially important for newly industrialised countries such as India where cities play a crucial role in socio-economic development.

Hyderabad is one of the fastest growing cities in India. It is located on the northern part of South India and is a capital of Andhra Pradesh state. With a population of 5.5 million people in 2001 it is the sixth largest city in India (Census of India 2001a). MCH also calculated future population scenarios for Hyderabad and estimate that 6.5 million people lived in HUDA in 2005; in 2011 Hyderabad will house 7.7 million people and in 2021 probably 10.8 million. The urban agglomeration can therefore be called a megacity by around 2020, whereas the scenarios for the wider urban agglomeration project a crossing of the 10 million mark by 2015 (MCH 2005).

The frequency and intensity of extreme rainfall events over Hyderabad, India, coupled with a barely adequate infrastructure and the shortcomings in implementation of land use planning in the city often cause devastating floods in the urban and periurban area. Hyderabad is considered to be a typical example of an emerging megacity where data on flood extents and their consequences are often unreliable and inconsistent or unavailable at all. Furthermore, there is little formalised information on the location and extent of the most exposed and vulnerable socio-economic entities such as the densely populated informal settlements as those are not represented in urban development plans. In the next sections we discuss the methodology and results of flood risk assessment in the city, combined with identification of informal settlements using lacunarity analysis of remote sensing data.

1. Flood risk assessment for Hyderabad

The potential hazards resulting in flooding of Hyderabad as an inland urban agglomeration are high inflows via surface water and extreme local rainfall events. The river Musi which traverses the city has a relatively small upstream basin area (its source lies only 90 kilometres to the west of Hyderabad) and is well regulated, posing a negligible threat presently and in the future. This was however not the case in 1908 when an extremely destructive flood hit the city. Reacting on this, in 1920 the Osman Sagar and in 1927 Himayat Sagar dam were constructed. These reservoirs reliably prevent the city from flooding by the Musi and are major drinking water sources.

The city is far less adapted to extremely intensive rainfalls over the urban agglomeration which occur due to the monsoon precipitation regime and are expected to occur even more frequently under future climate change. In Figure 1 on the left hand ordinate, we show the present distribution of daily rainfall at a station representative for the Hyderabad urban agglomeration (located at Begumpet, close to the former inner city airport). On the right hand ordinate the expected change until 2100 is depicted (under the A2 global CO2-emission scenario [11]), showing a strong increase of the frequency of intense rainfall events (IPCC 2000). This, together with the reported severe damages by strong rain events (Reckien et al. 2009) motivates to further analyse the spatially and socioeconomically explicit vulnerability towards this kind of flooding. A clear indication that slum areas are most vulnerable is the August 2000 event where 77 slums within the city area were completely washed away (IFRC 2000).

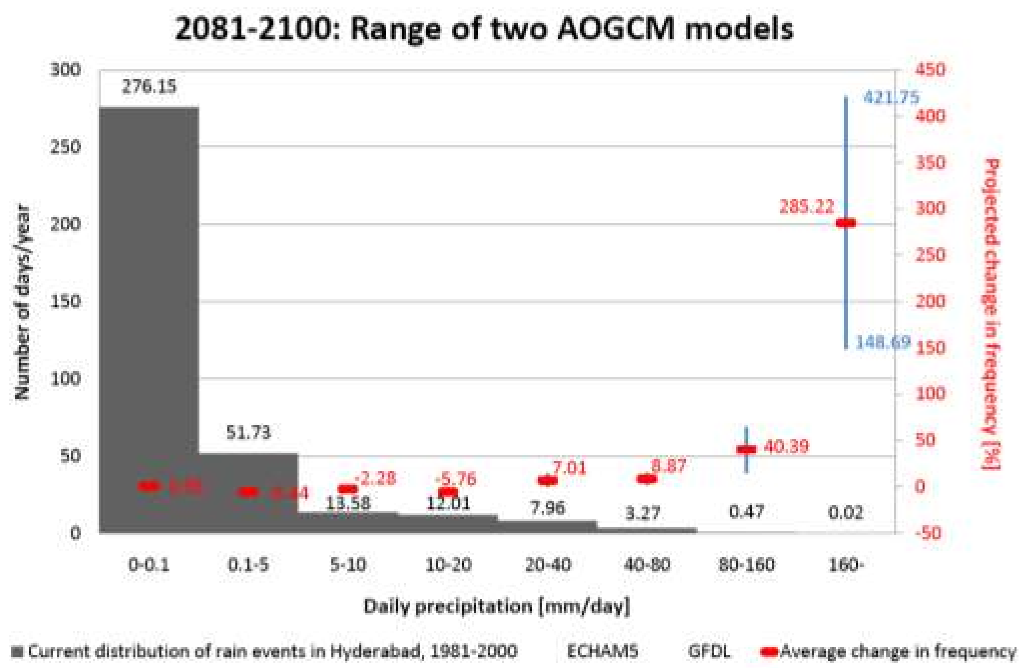


Figure 17. Current distribution of daily rainfall (left hand ordinate) and expected change (right hand ordinate) for Hyderabad/India.

2. Identification of flood prone areas

Low lying areas are frequently used as a first approximation for flood prone areas, e.g. in the context of sea level rise (Nicholls and Tol 2006). But this simple approach is inappropriate for assessing the impact of intensive rainfall events because here rapid water flows at the surface are generated which cause major damages - therefore a static analysis is insufficient. On the other hand, a full hydrodynamic model which represents water flows and their momentum is very demanding with respect to the details of the orography and the spatial and temporal pattern of the rainfall events. As an intermediate step we use here the so called flow accumulation map (Flacc, see e.g. Jenson and Domingue 1988) which describes the water flow at a particular location ("pixel") to be expected during a spatially homogenous strong rainfall event. It is calculated via the determination of the area of the upstream basin of the considered pixel, i.e. all locations are identified from where water flows to the considered pixel. From that it becomes clear that Flacc is a relative measure - the absolute amount of the flows depends on the rainfall intensity, but for any rain event double Flacc means double water flow through the pixel.

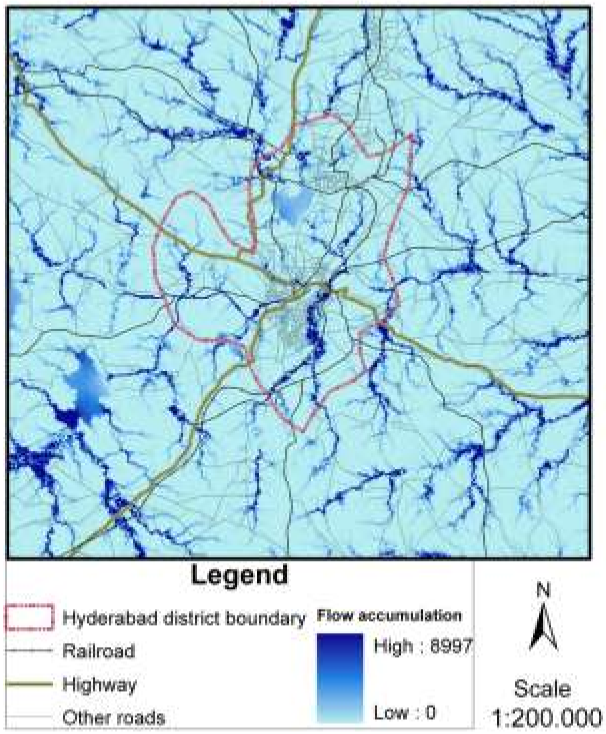


Figure 18. Flow accumulation map

As input data we used a DEM (digital elevation model) derived from the latest available version of SRTM dataset (Jarvis et al. 2008) and dealt with noise and errors in the data in the order of 2 meters by ignoring small orographic sinks which interrupt water flows artificially. After applying the respective algorithm to the DEM for the Hyderabad agglomeration area we obtained a map which reproduced the natural surface waters (reservoirs and rivers) perfectly and, additionally, shows us the net of water flows occurring under strong rain events (see Figure 18). Comparison against the artificial sewerage and storm water channels network showed that some of the calculated flow paths are regulated while others are not. The flow accumulation map also identifies vulnerable areas along the clogged or encroached channels.

3. Identification of location of informal settlements

Approximately 38% of Hyderabad's population are estimated to be living in informal settlements in 2006 (MCH 2005), with most of them being situated in rapidly growing outer municipalities. Confronted with high growth rates of the city, urban planners and administrators in Hyderabad require up-to-date information on city-wide land use patterns. Informal and often temporary character of slums often means that they are highly dynamic structures which are difficult to track using ordinary methods. Remote sensing hence is a swift and unbiased technique of land use data acquisition, while the methodology proposed in this paper describes a promising data analysis technique capable to make qualified spatially enabled statements on the location of informal settlements.

The definition of an informal settlement in India characterises it as a "compact area of poorly built congested tenements in an unhygienic environment usually with inadequate infrastructure and lacking proper sanitary and drinking water facilities" (Census of India 2001a). Such areas are frequently characterised by small dwelling units, narrow intrasettlement roads and high housing density – features which clearly distinct them from other residential neighbourhoods and make remote sensing an appropriate data acquisition method for slum recognition.

There were several attempts to perform informal settlement identification in India and particularly in Hyderabad using spectral radiance values only. Taubenböck et al. (2007) performed land cover change study in Hyderabad using supervised classification techniques. While this approach provided approximately 78% accuracy of recognition of built-up areas versus other land uses, this methodology was not capable to reliably distinguish between formal and informal settlements. Another study (Jain 2007) successfully used tonal variation in high spatial resolution data to identify rooftops within an isolated settlement which are characteristic for informal settlements in the Indian context, nevertheless acknowledging that this approach suffers from spectral noise and does not take into account morphological features of informal settlements.

Variability of materials used for roof constructions in informal settlements, extensive roof use for cloth drying or water storage equipment make identification of individual houses as a prerequisite of settlement density calculation in Indian urban context nearly impossible. A successful slum identification methodology must therefore take into account other properties of the surface, such as morphology and internal structure.

Cities can be considered to be complex systems composed of non-linear and multiple scale iterations of spatial and physical heterogeneous components (Amorim et al. 2009) and can be thus analysed by the means of fractal mathematics. Gefen et al. (1983) defined lacunarity as a measure the deviation of a geometric object, such as a fractal, from translational invariance, being a suitable indicator to measure spatial heterogeneity. Since lacunarity values represent the distribution of gaps within an image at various scales, it is considered to be a suitable and promising tool, capable to assess urban structure and isolate distinctive morphological features.

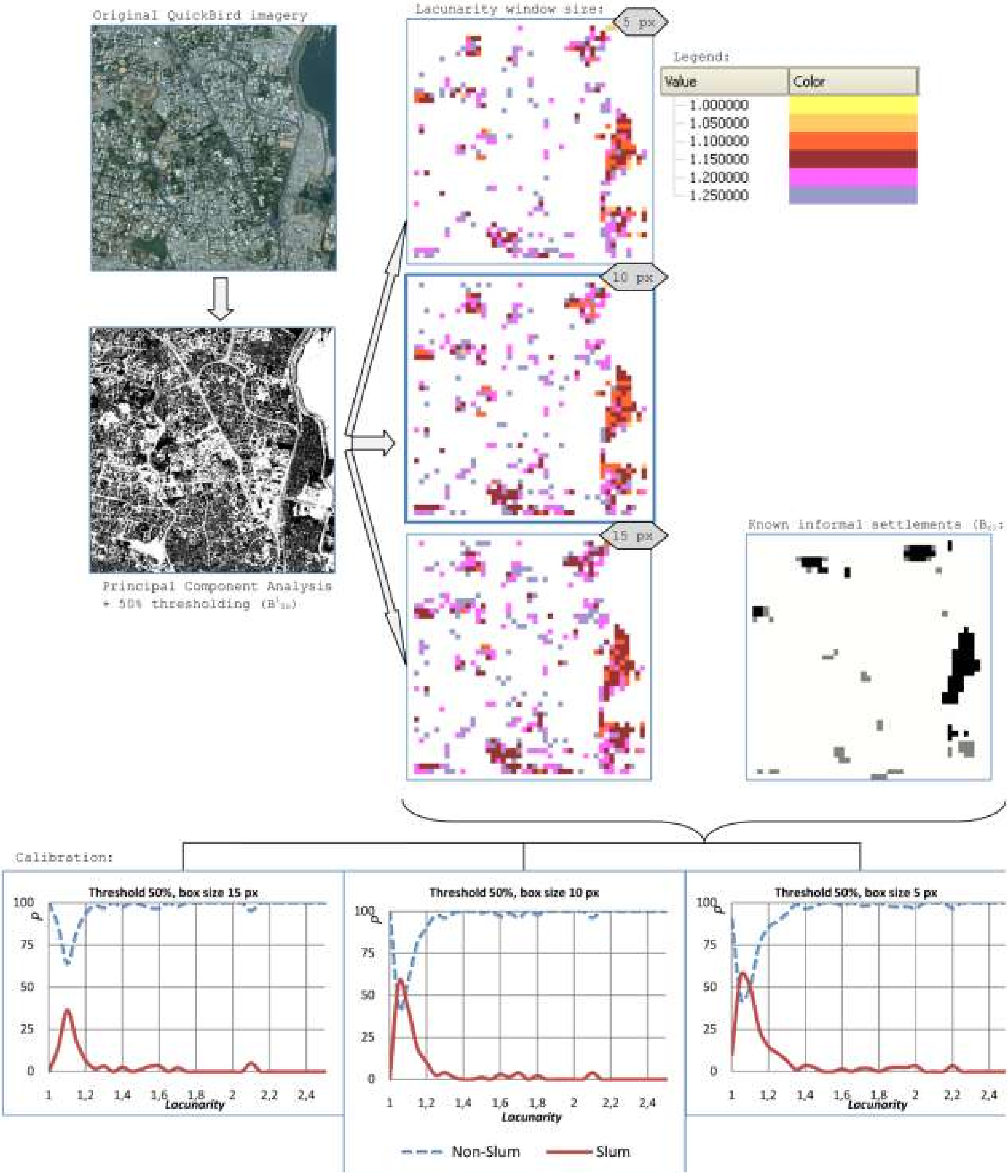


Figure 19. Informal settlements detection algorithm and its calibration (for details see text)

Figure 19 schematically represents the algorithm used for identification of informal settlements in Hyderabad. Two sets of cloudless QuickBird high resolution remote sensing imagery (acquired in March 2008) have been used in this study: image 1 which covers the 7.29 km^2 to the west of Hussain Sagar reservoir and contains Sanjeeviah Nagar slum has been used for algorithm calibration, while the equally large image 2 which covers the area to the east of Hussain Sagar is used for algorithm application and testing. First of all, Principal Component Analysis has been performed on the imagery, producing high contrast matrices M_1 and M_2 holding individual values stretching from 0 to 255 and clearly distinguishing between built areas and other land use types. Those matrices were then converted into binary datasets B^1_{48}, B^1_{50} and B^1_{52} using 48, 50 and 52 per cent thresholds respectively. Each matrix has been further split into 100 × 100 pixel blocks (approximately 60 × 60 m squares as per QuickBird resolution of 0.61 m) and for each of them the lacunarity value has been computed. We consider this box size to be an appropriate scale for identification of morphology of informal settlements, as it does accommodate fine scale intrasettlement structure while not considering large features which are more characteristic for industrial and formal residential areas.

Optimal moving window size has been empirically determined by calculating three lacunarity matrices for each binary matrix with moving window sizes 5, 10 and 15 pixels respectively (methodology adopted from Amazon forest classification by [9]). Since the area covered by M_1 was relatively well-studied during fieldwork in Hyderabad in November 2009 and March 2010, it was possible to construct a binary calibration dataset B^1_c, which describes the location of informal settlements and all other areas. Using B_c datasets as a mask, it became possible to calculate probabilities of each lacunarity in matrices B^1_{48} – B^1_{52} to belong to slum or non-slum class (Figure 19, bottom charts) and to conclude that the combination of 50% binarisation threshold and 10 pixel moving window size are optimal parameters for plausible identification of informal settlements in Hyderabad. This result is consistent with a previous study in this field (Barros Filho and Sobreira 2008), which showed that high spatial resolution satellite images from urban areas with better inhabitability conditions have higher lacunarity values than those with worse conditions.

Figure 20. Validation of slum detection algorithm (photo credit Martin Budde/PIK)

The empirically calibrated lacunarity calculation parameters were then applied to B^2_{50} matrix which was the “unknown territory” for the algorithm. As illustrated by Figure 20 and Figure 21, the algorithm has identified a large area of low lacunarity values in the upper left corner of the area of interest. Closer examination of the high resolution satellite imagery and analysis of ground truth data (Figure 20) have revealed that the identified area does indeed belong to a high-density settlement known locally as Bholakpur slum.

Since the suggested methodology is computing power intensive, the calculation of spatial distribution of informal settlements in Hyderabad has been not applied to the whole urban area of Hyderabad as yet. After this is done, its results will refine spatially undetermined official figures and greatly assist the planning and management processes in the city.

4. Conclusions

The comparison of flow accumulation maps and slum locations indicates high vulnerability to floods in the spots where informal settlements overlap with flow concentration areas. The proneness to floods of the Bholakpur slum as detected on the informal settlements map in Figure 21 (large red area in the upper part of the map) can be assessed as relatively low and can be certainly further reduced by appropriate urban planning and engineering measures. Risk of flooding and hence vulnerability is however significantly higher in the informal settlements along the Hussain Sagar surplus drainage channel and Ashok Nagar Road in the Chikkadpally neighbourhood (approximately 0.02 km^2 area in the lower central part of the Figure 21). This claim has been verified by the visual examination of the satellite photography which did reveal distinctive high density settlements on the banks of the drainage channel. As the frequency of extreme precipitation events in Hyderabad increases, so does the risk of increased water flow through the Hussain Sagar surplus drainage channel, thus endangering the long term survivability of weak informal structures on its banks if no flood defence infrastructure is in place.

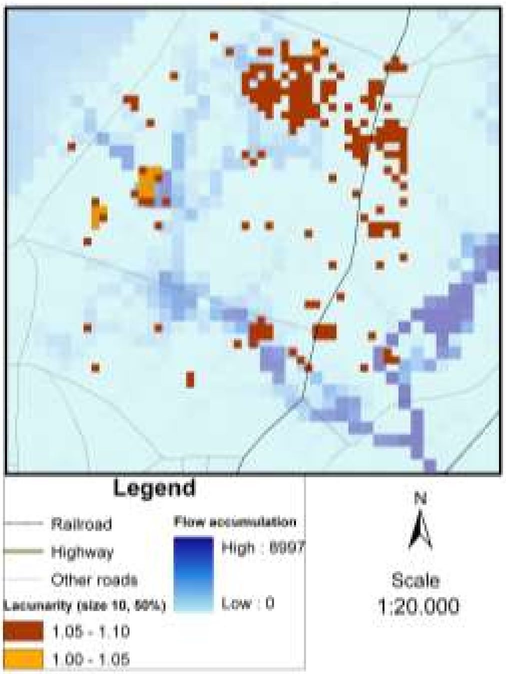


Figure 21. Vulnerability of informal settlements to floods

This result illustrates how the methodology developed in this paper can successfully identify hotspots of climate change vulnerability on the basis of satellite based globally available data sets. The calibration of the slum area identification algorithm requires additional knowledge of a small subarea of the urban agglomeration which includes known slum- and non-slum areas (B^1_c in Figure 19). It is quite possible that the calibration for Hyderabad works also for other Indian (or even developing world) urban agglomerations, but this will become clear during further applications. In our opinion, an important property of the suggested approach is its immediate transferability to other large urban agglomerations of the developing world and its independence on reliable large scale ground data.

Our first results corroborate the general statement that slums are often located in rainwater accumulation areas and frequently lack appropriate flood defence and rainwater drainage infrastructure. Even more importantly, it is possible to detect which slum areas will be most endangered by climate change and need most attention with respect to adaptation measures. Along the basic dimensions of adaptation to climate change, "accommodate - protect - retreat - avoid", the avoidance of new informal settlements in endangered areas would be an important option as slum areas are rapidly growing. This demands a better understanding where and why new slums will occur. Applying the presented slum area identification algorithm to past time slices of satellite imagery will constitute time series of the spatial slum distribution and allow for the development and testing of causal hypothesis of slum formation. Based on this empirically tested understanding preventive measures against informal settlements "at the wrong place" can be developed implying the establishment of adequate settlement alternatives.

Chapter VI: Conclusions

This research has laid down the foundations of a novel approach for rapid automated identification of slums in an urban context of India as exemplified by the megacity of Hyderabad. It is now possible to quickly and efficiently estimate current and past slum coverage in a city using unbiased satellite imagery data. The methodology, demonstrated by chapters II to V of this thesis, can be used to assess the performance of urban management practices and to validate the reporting on slum improvement programmes in Hyderabad and in other cities in India and beyond. The resulting datasets can be used to assess intra-urban vulnerability to climate change-induced floods.

Data acquisition has always been the underlying foundation of geographic science, be it discovery and description of new places on Earth or explanation of patterns of interactions between inhabitants of human settlements. While some geographic data, such as river length or the number of registered vehicles in a country is easily obtainable in simple and reliable ways, detailed and coherent data on human population structure in urban setting of developing countries is much more difficult to come by. Descriptive and explanatory research into the problem of urban slums has been particularly susceptible to data problems at global, national and local levels. Nevertheless, the knowledge on location, population as well as spatial and temporal aspects of slum development processes is extremely important to a broad spectrum of actors, ranging from urban planners and administrators to non-governmental organisations and profit-oriented enterprises.

This contribution presents a novel and efficient approach to solving the slum-related data problem using high resolution satellite imagery and advanced image manipulation and analysis methods.

1. Research questions answered

This thesis has addressed the research questions presented in Chapter I in the following manner:

Research question I: Is it possible to automatically identify slums in an Indian megacity, exemplified by Hyderabad, using remote sensing data? Is lacunarity appropriate for this?

Chapter II positively answered these questions by carrying out an exploratory study which served as a proof of concept, demonstrating that automated identification of slums in Hyderabad is possible and can be done using lacunarity-based methods.

A review of publications on the subject of automated satellite imagery-assisted slum recognition exposed the subject as a lively research area and identified several approaches to achieving the best results. These were roughly grouped into image classification, image morphology analysis and object detection-based ones. A lacunarity-based slum identification technique from the group of image morphology methods has been chosen as a suitable approach towards development of an automated slum identification algorithm for Hyderabad, and a series of tests has been conducted to identify the most appropriate pre-processing tools. The study compared principal component analysis and line detection-based imagery pre-processing approaches and found the latter one to provide superior results, thus defining the general direction of subsequent studies. It also experimented with a variety of parameters such as binarisation thresholds or sizes of lacunarity boxes and brackets and established the combinations which were the best in matching ground truth situation. Finally, the study identified optimum lacunarity ranges for slum identification purposes as 1.10 to 1.15.

Lacunarity, accompanied by line detection-based satellite imagery pre-processing routine has been found to be an appropriate method for identification of slums, producing an 83% slum detection rate over a test area in the central part of the city and highly plausible results for the rest of Hyderabad. The performance has been confirmed by ground truth surveys performed during research stays in Hyderabad in autumn 2009 and winter 2010. Application of this method has, for the first time, produced a coherent dataset describing the majority of informal settlements in

Hyderabad irrespective of organisational and political limitations. The resulting map agreed reasonably well with the scattered body of knowledge on slum locations in various parts of the city.

Research question II: Is it possible to use remote sensing data to assess the numbers of the people living in slums in Hyderabad and their spatial distribution? Can this improve the resolution of Census data and validate official slum population estimations?

The availability of newly generated high resolution satellite imagery-derived slum coverage data has enabled the computation of approximate slum population numbers for Hyderabad, expressed as statistical expectation values for individual election wards within a 400 km^2 area covering most of the city. The calculation combined automated slum identification results, coarse resolution census population data and a range of slum population densities derived from the literature.

To answer the given research question, high resolution aggregate statistics of slum population numbers within the city has been computed and the first census ward-level slum population map for Hyderabad has been created. This map has been found to be generally consistent with the coarse resolution census statistics and unofficial reports and identified high percentage of slum population in the north and the northwest of the city. Nevertheless, the study concluded that both over- and underreporting of slum population numbers does occur in Hyderabad, and provided an improved view on the slum distribution patterns within this urban agglomeration. The expectation value of the slum population share for the whole Municipal Corporation of Hyderabad has been calculated at 29%, thus assessing the officially recognised level of 35% for the whole city and up to 52% for some circles to be an unlikely high value.

Research question III: Is it possible to capture the dynamics of slum area change using multitemporal and multi-source satellite imagery? How to improve the robustness of the slum identification algorithm?

Automated processing and analysis of multitemporal and multi-source satellite imagery in slum identification context is a particularly challenging task because of changes in sun position, vegetation and sensor capabilities that strongly distort object/non-object signals across multiple images of the same area. To overcome this limitation, an improved pre-processing component of the slum identification algorithm which combines Canny and line segment detection techniques has been developed. The new method has produced two coherent and unbiased snapshots of Hyderabad's slum coverage in 2003 and 2010 and constituted the first ever successful attempt to automatically process multitemporal very high resolution satellite imagery of a whole city. Ground truthing of results has identified only one site out of twelve where the slum nature of the settlement type could not be confirmed, hence giving a positive answer to this research question. The analysis of slum locations for the whole city of Hyderabad in years 2003 and 2010 indicated a considerable growth of area occupied by slums between these years and allowed identification of trends in slum development on this urban agglomeration, namely densification of existing settlements, slum growth on the fringes and spatial focus of slum growth on the north and on the south of the city.

The robustness of the algorithm was improved by combining two advanced image processing tools (Canny and line segment detection) in a way that enabled rapid delineation of edges, exclusion of non-linear structures and ultimately allowed calculation of lacunarity as a proxy of slum probability in every of the approximately 260,000 of 3600 m^2 cells on a 2.6×10^9-pixel satellite image covering urban area of Hyderabad.

<u>Research question IV:</u> What are the possible impacts of future climate conditions on slum population of Hyderabad? Is it possible to use the slum identification algorithm in vulnerability assessment?

The analysis of the expected changes in climate patterns in the region of Hyderabad under the global A2 CO_2 emission scenario indicated a possible increase in frequency of severe precipitation events by the year 2100, while a local flow accumulation model provided insights into spatial distribution pattern of pluvial floods in the city. Together with the output of automated slum detection algorithm, this created necessary precondition for identification of vulnerability hotspots in the city. The analysis of several test areas in the city demonstrated that slums are frequently located in rainwater accumulation areas and, given the dismal flood defences and rainwater drainage infrastructure, their inhabitants are more vulnerable to pluvial floods than the average population of Hyderabad.

2. Application of results

The availability of a new satellite imagery assisted slum identification method will certainly contribute to the improvement of global and national multitemporal slum coverage and slum population statistics and advance our understanding of the slum development process in the world. Better availability of data will facilitate development of appropriate policies and efficient measurement of progress towards reaching Target 11 of the Millennium Development Goal 7: “By 2020, to have achieved a significant improvement in the lives of at least 100 million slum dwellers”.

On the national level, the data on the past and present of slums in the cities are indispensible for assessment of performance and identification of future emphases of urban infrastructure improvements and poverty alleviation programmes, such as the Rajiv Awas Yojana and Jawaharlal Nehru National Urban Renewal Mission in India or National Urban Sector Policy in Bangladesh. On the local level, the results are of tremendous importance to local governments, planning authorities, service providers and non-governmental organisations, as they will be provided with an additional unbiased source of data.

In case of Hyderabad, the results of slum identification and slum population assessment have been integrated into the Climate Assessment Tool for Hyderabad (CATHY) – a WebGIS-based urban decision support system developed at the Potsdam Institute for Climate Impact Research within the “Sustainable Hyderabad” project and intended for use by the Hyderabad Municipal Corporation Authority officials. At the time of writing of this thesis, CATHY is also being implemented as a public participation platform by members of civil society of Hyderabad, with the aim to facilitate collection and sharing of information on current weather-related vulnerabilities and future climate change adaptation actions. Satellite imagery-based slum location maps are one of the key features of CATHY. Apart from being available for consultation by decision makers and the general public, this data can be used for derivation of analytical datasets such as flood-induced vulnerability patters for Hyderabad under different climate change and socio-economic development scenarios, as illustrated by Figure 22. As a decision support system, CATHY is ready to be applied for checking urban planning decisions against their compatibility with future climate change.

Figure 22. Screenshot of CATHY WebGIS (source: own work)

During public meetings in Hyderabad city administrators expressed interest in using the results of this research in their daily work, but ultimately the pace of this process has been slowed down for political reasons, together with the final implementation of CATHY as an urban decision support system. One of the reasons for this was the fact that slums are an extremely sensitive political subject in Hyderabad. Many politicians see them as highly concentrated and easily exploitable voter banks, where political support can be easily won by implementation of minor infrastructure improvement projects or by offering temporary concessions.

The independent, satellite imagery-assisted evaluation of results of data collection procedures and counter-slum measures performed by local administration contradicts many official reports and is therefore barely beneficial in terms of performance assessment of local and regional government. Automated slum identification, augmented by ground truth surveys exposed inconsistencies in slum reporting in Hyderabad, namely that:

- Not all neighbourhoods classified as slums by the local government give the impression of a high density impoverished area, and
- Not all neighbourhoods that appear extremely impoverished and informal are officially known to the local government, nor are they recognised as slums.

The preliminary and final results of slum identification were frequently presented to governmental decision makers, academic institutions and civil society organisations during multiple project meetings in Hyderabad between 2010 and 2013. In 2013, a local newspaper featured an article about these findings, mentioning that they contradict the official view on slum share and the progress of slum elimination process (Deccan Chronicle, 2013). The assumption that informal settlements will vanish in due time in Hyderabad cannot be substantiated with current trend data – so adapting informal settlements to climate change may well be a major task the authorities have to deal with.

The work on the automated slum identification has been accompanied by an ethical question on the purpose of this research, namely: is it always good if the authorities of a city know exactly where the slums are and immediately get notified about establishment of slums within the city? This is undoubtedly true if the government has genuinely good intentions and sufficient means to prevent slum establishment while providing the citizens with an appropriate legal and institutional framework that would allow all urbanites to have decent living conditions. As this is often not the case, the application of this method to other cities and dissemination of identified slum coverage data must be pre-empted by careful analysis of the possible consequences.

3. Future perspectives

The automated slum identification methods presented in this thesis have been successfully applied to Hyderabad and produced results which are both scientifically novel and useful for decision makers in the city. The author sees great potential for future work in this field, particularly in the following directions:

- Application of the methodology to other urban agglomerations within Indian sub-continent and beyond, building upon the expression of interest by the University of Indonesia.
- Identification of different slum types (tent settlements, semi-permanent structures etc.).
- Integration with other urban morphology and land use analysis methods such as dynamic urban growth or vulnerability models,

The automated slum identification method presented hereby will deliver the best results when adjusted to the particularities of the structure of urban slums across countries and continents – a research direction which is yet to be thoroughly investigated. Nevertheless, even the current form of the algorithm is certainly capable to expand the horizon of knowledge on slums in the world and to provide a credible answer to the urging questions on the locations of slums in the world's cities.

It is worth mentioning that a very distinct feature of the work carried out within this PhD project is that it did not employ any proprietary software tools, meaning that the proposed slum identification methods are particularly suitable in financially tight situation of many cities in the global South. The computer code has been recently made available to a group of researchers from the University of Indonesia, who currently experiment with automated slum identification in a South-East Asian context.

Bibliography

1. Adusumilli, U. (2001). *Regulatory guidelines for urban upgrading: Hyderabad experience, India.* Paper presented at the First RGUU International Workshop held at Bourton on Dunsmore, United Kingdom, May 17-18, 2001.
2. Agarwal, S. (2011). The state of urban health in India; comparing the poorest quartile to the rest of the urban population in selected states and cities. *Environment and Urbanization,* Vol 23, No 1, 13-28.
3. Almeida, C. M., Oliveira, C. G., Rennó, C. D. & Feitosa, R.Q. (2011). Population estimates in informal settlements using object-based image analysis and 3D modelling. *IEEE Earthzine*, 16 August 2011.
4. Amorim, L., Barros Filho, M. N. & Cruz, D. (2009). Analysing Recife‘s urban fragments. In Koch, D., Marcus, L. & Steen, J. (Eds.), *Proceedings of the 7th International Space Syntax Symposium.* KTH, Stockholm, 003:1-14.
5. Awrangjeb, M., Ravanbakhsh, M. & Fraser, C. (2010). Automatic detection of residential buildings using LIDAR data and multispectral imagery. *ISPRS Journal of Photogrammetry and Remote Sensing* 65 (5), 457–467.
6. Awrangjeb, M., Zhang, C. & Fraser, C. (2012). Building Detection in Complex Scenes Thorough Effective Separation of Buildings from Trees. *Photogrammetric Engineering & Remote Sensing* 78(7), 729-745.
7. Bailly, J.S. & Levavasseur, F. (2012). Mapping of linear elements over cultivated landscape using VHSR data. PleiadesDay, 17-18 January, Toulouse, France.
8. Baltsavias, E. P. & Mason, S. (1997). Image-based reconstruction of informal settlements. In Gruen, A., Baltsavias E. P., & Henricsson O. (Eds.), *Proceedings of 17. International Workshop "Automatic Extraction of Man-Made Objects from Aerial and Space Images (II)", 5.-9. May, Ascona, Switzerland*. Birkhäuser Verlag, Basel, 87-96.
9. Barros Filho, M. N. & Sobreira, F. (2008). Accuracy of lacunarity algorithms in texture classification of high spatial resolution images from urban areas. *The International Archives of the Photogrammetry, Remote Sensing, and Spatial Information Sciences* 36, 417-22.
10. Baud, I., Kuffer, M., Pfeffer, K., Sliuzas, R. & Karuppannan, S. (2010). Understanding heterogeneity in metropolitan India: the added value of remote sensing data for analyzing sub-standard residential areas. *International Journal of Applied Earth Observation and Geoinformation* 12 (5), 359-374.

11. Baud, I., Pfeffer, K., Sridharan, N. & Nainan, N. (2009). Matching deprivation mapping to urban governance in three Indian mega-cities. *Habitat International* 33, 365–377.
12. Bhaskaran, S., Paramananda, S. & Ramnarayan, M. (2010). Per-pixel and object-oriented classification methods for mapping urban features using Ikonos satellite data. *Applied Geography*, 30(4), 650-665.
13. Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensin,* 65(1), 2-16.
14. Bong, D., Chun Lai, K. & Joseph, A. (2009). Automatic Road Network Recognition and Extraction for Urban Planning. *International Journal of Applied Science, Engineering and Technology* 5 (1), 209-215.
15. Bostel, F. (2012). Validierung und Kalibrierung von remote-sensing basierten Temperatur- und Siedlungsstrukturdaten für die urbane Agglomeration Hyderabad/Indien. Bachelor Thesis, Albert-Ludwig University Freiburg, 60 pp.
16. Canny, J. (1986). A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 8(6), 679-698.
17. Carr-Hill, R. (2013). Missing Millions and Measuring Development Progress. *World Development* 46, 30–44.
18. Census of India (2001). Metadata and Brief Highlights on Slum Population [online]. Available from http://censusindia.gov.in/Data_Products/Data_Highlights/ Data_Highlights_link/metadata_highlights.pdf [accessed 5th July 2011].
19. Census of India (2001a). (Provisional) slum population - explanatory note [online]. Available from http://censusindia.gov.in/Tables_Published/Admin_Units/Admin_links/slumnote.html [accessed 2nd February 2011].
20. Census of India (2001b). (Provisional) slum population in million plus cities (municipal corporations): part A [online]. Available from http://censusindia.gov.in/Tables_Published/Admin_Units/Admin_links/slum1_m_plus.html [accessed 7th February 2011].
21. Centre for Good Governance (2008). Survey of Child Labour in Slums of Hyderabad: Final Report. Hyderabad, India, 17 December 2008.
22. Chapligin, B. (2006). Assessment of the hydrochemical groundwater status and its relation to an integrated urban water system model based on an urban slum and a rural area in Hyderabad, India. Unpublished Diploma thesis, Department of Applied Geography University of Karlsruhe, Germany.

23. Cheng, P., Toutin, T. & Zhang, Y. (2003). QuickBird – geometric correction data fusion and automatic DEM extraction. *Earth Observation Magazine* 11(4), 14-18.
24. Davis, M. (2006). *Planet of slums*. London: Verso.
25. Deccan Chronicle (2013). Hyderabad has fewer slums than is claimed: German study. 18 February 2013.
26. Dewan, A.M. & Yamaguchi, Y. (2009). Land use and land cover change in Greater Dhaka, Bangladesh: using remote sensing to promote sustainable urbanisation. *Applied Geography* 29, 390-401.
27. Ellefsen, R., Swain, P. H. & Wray, J. (1973). Urban land-use mapping by machine processing of ERTS-1 multispectral data: a San Francisco Bay area example. In *Proceedings of the Conference on Machine Processing of Remotely Sensed Data*. Purdue University, West Lafayette, pp. 2A2-2A22.
28. Ferré, C., H.G. Ferreira, F.H.G. & Lanjouw, P. (2012). Is There a Metropolitan Bias? The relationship between poverty and city size in a selection of developing countries. *World Bank Econ Rev* 26(3), 351-382.
29. Fugate, D., Tarnavsky, E. & Stow, D. (2010). A survey of the evolution of remote sensing imaging systems and urban remote sensing applications. In Rashed, T. & Jürgens, C. (Eds.), *Remote sensing of urban and suburban areas*. Netherlands, Dordrecht: Springer, 119-139.
30. Gefen, Y., Meir, Y., Mandelbrot, B. & Aharony, A. (1983). Geometric implementation of hypercubic lattices with noninteger dimensionality by use of low lacunarity fractal lattices. *Physical Review Letters* 50(3), 145-148.
31. GHMC (2009). Statement showing ward wise population and delimitation of election wards in Greater Hyderabad [online]. Available from http://www.ghmc.gov.in/ tender%20pdfs/election_wards.pdf [accessed 5th December 2011].
32. GHMC (2005). City Development Plan. Greater Hyderabad Municipal Corporation, Hyderabad, India.
33. GHMC (2010) Revised master plan for core area (erstwhile MCH area) of GHMC. Greater Hyderabad Municipal Corporation Report No. 3650, Hyderabad, India.
34. von Gioi, R.G., Jakubowicz, J., Morel, J.M. & Randall, G. (2012). LSD: a line segment detector. *Image Processing On Line*, 24 March, 2012.
35. Goel, S. L. & Dhaliwal, S. S. (2002). *Urban development and management.* New Delhi: Deep and Deep Publications.

36. Government of India (2010a). Government sets up an eight member expert committee to examine the draft Rajiv Awas Yojana. Government of India, Press Information Bureau, Mumbai.
37. Government of India (2010b). *National Sample Survey 65th Round (2008-2009).* Ministry of Statistics and Programme Implementation, New Delhi, India.
38. Government of India (2010c). *Report of the Committee on Slum Statistics/Census*. Ministry of Housing and Urban Poverty Alleviation, New Delhi, India.
39. Graesser, J., Cheriyadat, A., Vatsavai, R.R., Chandola, V., Long, J. & Bright, E. (2012). Image Based Characterization of Formal and Informal Neighborhoods in an Urban Landscape, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 5(4), 1164-1176.
40. Grigillo, D., Fras, M. & Petrovič, D. (2012). Automated building extraction from IKONOS images in suburban areas*. International Journal of Remote Sensing*. 33 (16), 5149-5170.
41. Gunn, S. (1999). On the discrete representation of the Laplacian of Gaussian. *Pattern Recognition* 32 (8), 1463–1472.
42. Helmerich, J., Moid, M., Hanish, M. & Wulf, B. (2007). Achieving sustainable food security and poverty reduction through consumer cooperatives in Hyderabad. Working paper 36910, Humboldt University Berlin, Institute for Agricultural Economic and Social Sciences.
43. Herold, M., Goldstein, N. C. & Clarke, K. C. (2003). The spatiotemporal form of urban growth: measurement, analysis and modeling. *Remote Sensing of Environment* 86 (3), 286-302.
44. HMDA (2011). The Metropolitan Development Plan 2031. Hyderabad Municipal Development Authority, Hyderabad, India.
45. Hofmann, P., Strobl, J., Blaschke, T. & Kux, H. (2008). Detecting informal settlements from Quickbird data in Rio de Janeiro using an object based approach. In Blaschke, T., Lang, S., Hay, G.J. (Eds.), *Object-based Image Analysis*, Springer, 531-553.
46. HUDA (2003). Hyderabad 2020: A plan for sustainable development. Hyderabad Urban Development Authority, Hyderabad, India, 322 pp.
47. Hurskainen, P. & Pellikka, P. (2004). Change detection of informal settlements using multi-temporal aerial photographs – the case of Voi, SE Kenya. Paper presented at the 5th AARSE conference (African Association of Remote Sensing of the Environment), 18-21 October, 2004, Nairobi.

48. IFRC (2000). Flash floods submerge communities in Hyderabad. International Federation of Red Cross and Red Crescent Societies, 4th September. Available from http://www.reliefweb.int [accessed 19th May 2010].
49. IPCC (2000). Special Report on Emissions Scenarios. A Special Report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, 612 pp.
50. Jain, S. (2007). Use of IKONOS satellite data to identify informal settlements in Dehradun, India. International *Journal of Remote Sensing* 28(15), 3227 - 3233.
51. Jarvis, A., Reuter, H.I., Nelson, A., & Guevara, E. (2008). Hole-filled SRTM for the globe Version 4, available from the CGIAR-CSI SRTM 90m Database [online]. Available from http://srtm.csi.cgiar.org [accessed 20 May 2010].
52. Jensen, J.R. & Cowen, D.C. (1999). Remote sensing of urban/suburban infrastructure and socioeconomic attributes. *Photogrammetric Engineering and Remote Sensing*, 65, 611–622.
53. Jenson S.K. & Domingue J.O. (1988). Extracting Topographic Structure from Digital Elevation Data for Geographic Information System Analysis. *Photogrammetric Engineering and Remote Sensing* 54(11), 1593-1600.
54. Khelifa, D. & Mimoun, M. (2012). Object-based image analysis and data mining for building ontology of informal urban settlements. In Bruzzone, L. (Ed.), *Proc. Image and Signal Processing for Remote Sensing* XVIII 8537.
55. Kit O., Lüdeke M. & Reckien D. (2011). Assessment of climate change-induced vulnerability to floods in Hyderabad/India using remote sensing data. In Otto-Zimmermann, K. (Ed.), *Resilient Cities - Cities and Adaptation to Climate Change, Local Sustainability*, 1(2), 35-44.
56. Kit, O. (2013). Planning the city of tomorrow for the climate of tomorrow: applying Climate Assessment Tool for Hyderabad. “Sustainable Hyderabad” Project Policy Brief Discussion Series 01.
57. Kit, O., Lüdeke, M. & Reckien, D. (2012). Texture-based identification of urban slums in Hyderabad, India using remote sensing data. *Applied Geography* 32 (2), 660-667.
58. Kit, O., Lüdeke, M. & Reckien, D. (2013). Defining the bull's eye: satellite imagery-assisted slum population assessment in Hyderabad, India. *Urban Geography* 34(3), 413-424.
59. Kohli, D., Sliuzas, R., Kerle, N. & Stein, A. (2012). An ontology of slums for image-based classification. Computers, *Environment and Urban Systems* 36 (2) 154–163.

60. Kundu, A. (2011). *Trends and processes of urbanisation in India*. Human Settlements Working Paper 34, IIED, London, United Kingdom.
61. Lillesand, T. (1990). Satellite remote sensing: its evolution and synergism with GIS technology. *Government Information Quarterly* 7(3), 307-327.
62. Lo, C. P. & Welch, R. (1977). Chinese urban population estimates. *Annals of the Association of American Geographers* 67(2), 246-253.
63. Lüdeke, M. K. B., Budde, M., Kit, O. & Reckien, D. (2010). Climate Change Scenarios for Hyderabad: integrating uncertainties and consolidation. Emerging megacities V1/2010, 37 pp.
64. Maktav, D., Erbek, F. S. & Jürgens, C. (2005). Remote sensing of urban areas. *International Journal of Remote Sensing* 26(4), 655-659.
65. Malhi, Y. & Román-Cuesta, R. (2008). Analysis of lacunarity and scales of spatial homogeneity in IKONOS images of Amazonian tropical forest canopies. *Remote Sensing of Environment* 112(5), 2074-2087.
66. Marr, D. & Hildreth, E. (1980). Theory of edge detection, Proc. Roy Soc. Lond 207, 187-217.
67. Martinez, K. & Cupitt, J. (2005) VIPS – a highly tuned image processing software architecture. In *Proceedings of the IEEE International Conference on Image Processing, Sept. 2005, Genoa.* pp. 574-577.
68. MCH (2005). *Draft City Development Plan.* Municipal Corporation of Hyderabad, Hyderabad.
69. Miller, R.B. & Small, C. (2003). Cities from space: potential applications of remote sensing in urban environmental research and policy. *Environmental Science & Policy*, 6 (2), 129–137.
70. Muchoney, D. M. & Haack, B. N. (1994). Change detection for monitoring forest defoliation. *Photogrammetric Engineering & Remote Sensing* 60, 1243-1251.
71. Myint, S. & Lam, N. (2005). A study of lacunarity-based texture analysis approaches to improve urban image classification. *Computers, Environment and Urban Systems* 29(5), 501-523.
72. Myllylä, S. (2001). Street Environmentalism. Civic associations and environmental practices in the urban governance of third world megacities. *Acta Electronica Universitatis Tamperensis* 91, Tampere, Finland.
73. Naidu, R. (1990). Old cities, new predicaments: a study of Hyderabad. Sage, London and New Delhi, 177 pp.

74. Nicholls, R. & Tol, R. (2006). Impacts and responses to sea-level rise: a global analysis of the SRES scenarios over the twenty-first century. *Phil. Trans. R. Soc. A* 15 (364) no. 1841, 1073-1095.
75. Niebergall, S., Loew, A. & Mauser, W. (2008). Integrative assessment of informal settlements using VHR remote sensing data – the Delhi case study. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 1(3), 193-205.
76. Nolte, E.-M. (2010). The application of optical satellite imagery and census data for urban population estimation: A case study for Ahmedabad, India. PhD thesis, Karlsruhe Institute of Technology, Karlsruhe, Germany.
77. Owen, K. & Wong, D. (2013). An approach to differentiate informal settlements using spectral, texture, geomorphology and road accessibility metrics. *Applied Geography* 38, 107-118.
78. Patino, J.E. & Duque, J.C. (2013). A review of regional science applications of satellite remote sensing in urban settings. Computers, Environment and Urban Systems, 37, 1–17.
79. Peeters, A. & Etzion, Y. (2012). Automated recognition of urban objects for morphological urban analysis. *Computers, Environment and Urban Systems* 36 (6), 573–582.
80. Poulain, V., Inglada, J., Spigai, M., Tourneret, J.-Y. & Marthon, P. (2011). High-resolution optical and SAR image fusion for building database updating. *IEEE Transactions on Geoscience and Remote Sensing*, 49 (8), 2900-2910.
81. Reckien, D., Hofmann, S. & Kit, O. (2009) Qualitative climate change impact networks for Hyderabad/India. Report for the Project: Hyderabad as a Megacity of Tomorrow: Climate and Energy in a Complex Transition towards Sustainable Hyderabad – Mitigation and Adaptation Strategies by Changing Institutions, Governance Structures, Lifestyles and Consumption Patterns.
82. Rhinane, H., Hilali, A., Berrada, A. & Hakdaoui, M. (2011). Detecting Slums from SPOT Data in Casablanca Morocco Using an Object Based Approach. *Journal of Geographic Information System* 3(3), 217-224.
83. Richards, J. A. & Jia, X. (2006). *Remote Sensing Digital Image Analysis.* Springer-Verlag, Berlin, 439 pp.
84. Risbud, N. (2010). Typology of Slums and Land Tenure in Indian Cities. Presentation at the National Workshop on Land Tenure Issues in Slum Free Planning, Ahmadabad, India, August 30, 2010.

85. Rozenstein, O. & Karnieli, A. (2011) Comparison of methods for land-use classification incorporating remote sensing and GIS inputs. *Applied Geography* 31 (2011) 533-544.
86. Satterthwaite, D. (2004). The under-estimation of urban poverty in low- and middle-income nations. Poverty Reduction in Urban Areas Working Paper 14, IIED, London, United Kingdom.
87. Satterthwaite, D. (2010). Urban myths and the mis-use of data that underpin them. In Beall, J., Basudeb, G.-K. & Kanbur, R. (Eds.), *Urbanization and Development: Multidisciplinary perspectives*. Oxford University Press, Oxford, United Kingdom, pp. 83-101.
88. Sengupta, S. (2009). Of bungalows and bastis of Banjara Hills. The Times of India. 13 November 2009.
89. Shashi Mohan, B. & Vijaya Lakshmi, T. (2012). Development of Slum Information System for Planning and Governance of Urban Areas Using Geomatics. Proc. 6th International Symposium on Advances in Science and Technology, Kuala Lumpur, Malaysia, 24-25 March. 11 pp.
90. Shekhar, S. (2012). Detecting slums from QuickBird data in Pune using an object-oriented approach. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 39 (8), 519-524.
91. Short, J., Kim, Y., Kuss, M. & Wells, H. (1996). The dirty little secret of world cities research. *International Journal of Urban and Regional Research*, 20, 697–717.
92. Sliuzas, R., Mboup, G. & de Sherbinin, A. (2008). Report of the expert group meeting on slum identification and mapping. Report by CIESIN, UN-Habitat, ITC, p. 36.
93. Stoler, J., Daniels, D., Weeks, J.R., Stow, D.A., Coulter, L.L. & Finch, B.K. (2012). Assessing the utility of satellite imagery with differing spatial resolutions for deriving proxy measures of slum presence in Accra, Ghana. *GIScience & Remote Sensing*, Vol. 49, No 1.
94. Taubenböck, H. & Kraff, N.J. (2013). The physical face of slums: a structural comparison of slums in Mumbai, India, based on remotely sensed data. *J Hous and the Built Environ*, online first.
95. Taubenböck, H., Pengler, I., Schwaiger, B., Cypra, S., Hiete, M. & Roth, A. (2007). A multi-scale urban analysis of the Hyderabad Metropolitan area using remote sensing and GIS. In: Urban Remote Sensing Joint Event, Paris, France.
96. The Community Studies Team (2007): Food and Nutritional Security in the Slums of Hyderabad [online]. Available from http://www.sustainable-hyderabad.de/index.php?page=workingpapers [accessed 8 May 2011].

97. The Times of India (2012). World Bank team visits Hyderabad slums. 12 June.
98. The Times of India (2013). Slum pocket a nightmare for Jubilee Hills residents. 15 February.
99. Thomson, C. (2000). Remote sensing/GIS integration to identify potential low-income housing sites. *Cities* 17(2), 97-109.
100. UN (2003). *The challenge of slums - global report on human settlements.* United Nations Human Settlements Programme, Nairobi.
101. UN (2006). *State of the world's cities report 2006/7.* United Nations Human Settlements Programme, Nairobi.
102. UN (2009). *World urbanization prospects. The 2009 revision.* Population Division, Department of Economic and Social Affairs, United Nations Secretariat, New York.
103. UN (2011a). *UN data glossary* [online]. Available from http://data.un.org/Glossary.aspx [accessed 2nd February 2011].
104. UN (2011b). *The economic role of cities.* The global urban economic dialogue series. United Nations Human Settlements Programme.
105. UN (2012). *The future we want: Cities.* Factsheet produced by United Nations Department of Public Information at Rio+20 UN Conference on Sustainable Development.
106. Ünsalan, C. (2009). Statistical, structural, hybrid, and graph theoretical features to measure land development. *IEEE Geoscience and Remote Sensing Letters* 6 (1), 72-76.
107. Veljanovski, T., Kanjir, U., Pehani, P., Oštir, K. & Kovačič, P. (2012). Object-Based Image Analysis of VHR Satellite Imagery for Population Estimation in Informal Settlement Kibera-Nairobi, Kenya. In Escalante-Ramirez, B. (Ed.), *Remote Sensing – Applications*. InTech. pp. 407-436.
108. Wakode, H.B., Baier, K., Jha, R. & Azzam, R. (2013). Analysis of urban growth using Landsat TM/ETM data and GIS—a case study of Hyderabad, India. *Arabian Journal of Geosciences*, January 2013.
109. Weeks, J.R., Hill, A. G., Stow, D. A., Getis, A. & Fugate, D. (2007). Can We Spot a Neighborhood From the Ground? Defining Neighborhood Structure in Accra, Ghana. *Geojournal* 69, 9–22.
110. Weizman, L. & Goldberger, J. (2009). Urban-Area Segmentation Using Visual Words. *IEEE Geoscience and Remote Sensing Letters* 6(3), 388-392.
111. Zhan, Q., Shi, W. & Xiao, Y. (2005). Quantitative analysis of shadow effects in high-resolution images of urban areas. *ISPRS Archives* 36-8.